AN ANALYSIS OF IN-TRANSIT LEAD TIME FOR ASSET

DELIVERY AT OGDEN AIR LOGISTICS CENTER

THESIS

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AFIT/GLM/LSM/89S-49

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Abstract

Maintenance Inventory Centers (MICs) are forward stockage points for Depot Maintenance (MA) activities. AFLC has directed that the amount of material stocked in MICs be reduced. The in-transit delivery time for replenishment issues to MICs from Depot Supply has significant impact on material support concurrent with minimizing inventory levels. This study examined MIC stock replenishment in-transit time. In-transit times experienced during a six-month period in six MICs at Hill AFB, Utah (Ogden ALC) were analyzed to establish performance parameters for simulation analyses. Also, quality control tools to reduce the in-transit time and associated variability were also investigated.

Empirical in-transit time performance statistics implied the AFLC 1.5 working day delivery time standard for MIC replenishment issues was not being achieved for all MICs. Fitting empirical data to theoretical probability distributions for use in subsequent simulation experiments supported previous research that lead time data is occasionally so variable that it may not fit familiar theoretical probability distributions.

Simulation experiments indicated that the 95% line item fill rate objective outlined in certain MA data automation reports is achievable only for items characterized by high frequency of demand. The mean, variance, and probability distribution of in-transit delivery time, coupled with the current 15/7 day (stock level/reorder point) inventory policy were the main factors influencing inventory performance. Reducing the mean in-transit

time improved material availability in a MIC characterized by beta-distributed in-transit delivery times.

The labor-intensive data collection required to measure the delivery process with currently available data sources is an obstacle to timely, reliable, and proactive control over the delivery process. Planned automated data systems such as the Stock Control and Distribution System must incorporate reliable and timely measurement of a MIC replenishment order's progress through the order cycle.

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I. Introduction

General Issue

In order to assure adequate material support to Air Force Depot Maintenance efforts, Maintenance Inventory Centers (MICs) have been established in most major work centers at the five Air Logistics Centers (ALCs) and two specialized repair facilities in the Air Force Logistics Command (AFLC). The MIC is a forward stockage point owned and operated by Depot Maintenance activities that provides interim storage of material for subsequent issue to support the production effort. The number of MICs at each ALC, as well as their location, are determined by the local Directorate of Maintenance (MA) (22:112). AFLC has recently attempted to reduce the amount of material held in the MICs. General Alfred G. Hansen, Commander of AFLC, stated that one of the reasons the command had a "banner year" in Fiscal Year (FY) 1988 was that the MICs were now addressing problems with excess stockage of material (13:10). An example of initiatives in this area can be seen from the experience at Oklahoma City ALC (OC-ALC) at Tinker AFB, OK, as outlined in AFLC Pamphlet 66-65, Depot Maintenance Annual Report FY 88:

> An excess pseudo Maintenance Inventory Center (MIC) has been established within the Directorate of Maintenance for the controlled credit return of non-credit expense material to

> the Directorate of Distribution. Material, declared excess as a result of no usage in the past seven months and no [anticipated] future requirements for the next three quarters, is transferred to the Excess MIC. The Command directed a reduction of the MIC stock level from thirty days to fifteen days. By turning the material over to the Excess MIC, MA could effectively draw down the MIC stock levels and monitor both types of excesses for credit turn-ins (Year-to-Date savings of $185,000). At the same time, some of this excess material has been reissued from the Excess MIC to other MA MICs who have a valid requirement. This last action has actually saved MA what would have been a non-credit turn-in and the cost of the material request (Year-to-Date savings of $240,000) in Material Requests. Based on the months the excess MIC has existed the total FY 88 material savings was $424,000. (5:64-65)

However, the in-transit delivery time of the actual ordering, movement, and receipt of material in the MICs from the Depot Supply function may have significant impact on efforts to assure high levels of material support, while at the same time minimizing inventory levels. Since nearly 48% of the Depot Maintenance Service, Air Force Industrial Fund (DMS, AFIF) budget allocated by the federal government to AFLC in FY 1988 was spent towards material support, cutting expenditures in this area is a lucrative target. On the other hand, lack of material is a major cause of work stoppage in Depot Maintenance activities, and failing to have adequate amounts of stock on hand when needed can cause wasted expenditures in idle man-hours and impede productivity (20).

<u>Review of Existing Policy for MIC Stockage and Delivery</u>

<u>MIC Stockage Policy</u>. McBride explained three "routes" in which Depot Maintenance (MA) receives material support in his AFIT thesis <u>Depot Maintenance Parts Demand Distribution and Evaluation of Alternative Stockage Policies</u>:

1. The first route is where the MIC issues material from on-hand inventories to MA production activities. The MIC is then in turn replenished from Depot Supply (DS) stocks as required. In this first route, the item is stocked both in the MIC and at DS. Items replenished through this route will be the primary focus of this study (22:10).

2. The second route is where material support is provided solely by DS, and the item is not stocked in the MIC. An item may not be stocked in the MIC because it is too large to store, or it requires special security or environmental controls, or demand for the item is so infrequent that stockage in the MIC is not justified (22:10).

3. The third route that MA receives material support for production line requirements is where the item is solely stocked in the MIC, with no additional stocks held in DS. This generally occurs in the case of locally manufactured or locally purchased parts used exclusively by activities supported by the MIC (22:10).

For items stocked in the MICs, a recommended stockage objective is computed every seven days by the Exchangeables Production System (EPS), also known as the G402A Data System. AFLC Manual 66-411, Volume Three, <u>The Exchangeables Production System (G402A) Users Manual, (Material Support),</u> describes the system as:

> The Exchangeables Production System (EPS) was designed to furnish Depot Maintenance with an on-line, real-time system. This system is designed to allow Production Support (PSF) personnel, Indirect Material Function (IMF) personnel, and Maintenance Inventory Center (MIC) personnel the ability to order and issue needed material and also allow them the ability to track and file maintain their own transactions.

This system provides them with the capability to update data by processing material requirements, issues, turn-ins and correcting transactions; then to retrieve this information through means of a CRT terminal and remote printers. The system provides visibility of MIC requirements for direct/indirect material issues/turn-ins. (7:5)

Two of the primary questions to answer when formulating inventory stockage policy are: 1) How much to order?, and 2) When to order (27)? These two questions can be answered by determining the appropriate stockage level (or "how much to order"), and reorder point (or "when to order") for each item to be stocked. AFLCR 66-53, Maintenance Material Control, defines stockage level as the computed requirement for stockage of an item based on some predetermined formula or management judgement that may take into account past and possibly future planned usage of a given item (8:9). The reorder point is defined as the stock position, or amount of on-hand stock, at which replenishment is required to assure continued availability of a given item (8:8).

At the time of McBride's study, HQ AFLC guidance to their Depot Maintenance activities for MIC stockage objectives and reorder points was:

> MIC material will be stored in quantities sufficient to meet production requirements, but not to the extent that excesses will generate. To assist in maintaining a balanced stockage position, each item has a system computed stockage level or a manually established minimum special level and a system computed retention level.
>
> Each week, the G402A computes a MIC stock level for a MIC stockage for all NSNs [National Stock Numbers] on the MIC detail. A 30-day stockage for expense material ERRC [XB3 or XF3] and a 15-day level for investment material ERRC [XD2] coded assets. MIC personnel will initiate the MIC replenishment transaction at the 50 percent level of stockage objective, or

earlier if experience indicates additional order and ship time is required. (22:11)

ERRC is an acronym that refers to the "Expendability, Recoverability, Reparability, Cost" code, which indicates the level of repair of Air Force Items (22:110;10:3-114). The basic distinction between ERRC XB3, XF3 and XD2 items lies in the relative level of repair capability established for these items. Recoverable material (XD2) is considered more economical to repair than to replace when it fails. Extensive depot-level repair capabilities exist for almost all XD2 items. A much more limited repair capability is established for XB3 and XF3 (also known as consumable) items, on the other hand. These items are actually condemned and disposed of at base-level because it is more economical to obtain another item rather than repair the broken asset (10:3-114).

In general, only about 30 days worth of expense material, and 15 days worth of investment material should be stocked in the MICs according to the policy outlined above. According to AFM 67-1, Volume II, Part Two, whether an asset is an expense or investment item is dependent upon the item's monetary value and, usually, the source of funding. An investment item is normally more expensive relative to an expense item. Also, when supply issues an investment item, some form of accountability for the asset must be maintained. In contrast, either greatly reduced or no accountability is required for expense items once they are issued to users (10:3-114). Furthermore, expense material is financed and managed under the Air Force stock fund. Expense items are charged as an expense to the Depot Maintenance Service, Air Force Industrial Fund when issued from DS to MA organizations (8:6). Investment items, on the other hand, are normally recoverable assemblies, modification kits, or other material that are charged to the System Support Division of the Air Force stock fund (483,6).

The EPS computes MIC stockage levels based on an average Daily Demand Rate (DDR) multiplied by a specified number of days stockage, either 30 or 15 (22:12). The DDR represents a theoretical average usage of a given part per day. The DDR is derived by dividing the stock level factor (or accumulated demands in units) by the number of accumulated days of demand experience (or Days Experience, DE) (22:14). Additionally, there are some items stocked in the MIC that have stockage objectives and reorder points computed based both on the DDR logic described above, and on projected demands for higher level end-items. These items, known as planned material, were not evaluated in McBride's effort, and the same restriction holds for this effort as well (22:12).

AFLC Manual 66-411, Volume Three outlines additional logic for stockage computations:

> The recommended stockage is computed in the system every seven days to determine the new 30 day requirement. There are several ways the system computes the recommended stockage which are explained [below]:
>
> (1) If the NSN is not planned and has 6 months or more of issue history, the system will compute the stockage using the simple average of the last six months for the 30 day recommended stockage.
>
> (2) If the NSN is not planned and has less than 6 months of issue history, the system will compute the stockage using the simple average of the months available for the 30 day recommended stockage
>
> (3) If the NSN is planned the system will use the issue history simple average times 0.5 plus the 30 day requirement

for the end-item computation, times 0.5, using this for the 30 day requirement. (7:32)

However, in June 1988, HQ AFLC directed a change to the 30/15 day stockage computation practice. Due to reductions in the Depot Maintenance Service, Air Force Industrial Fund (DMS, AFIF), the primary source of federal funding for AFLC functions, each ALC Director of Maintenance was instructed to reduce on-hand inventories and funding obligations on backordered items. To do this, each ALC was directed to draw down the MICs to 15 day stockage levels for all items, regardless of whether the item was consumable or recoverable, expense or investment (ERRC items XB3, XF3, or XD2). Also, MIC stock replenishment would not take place until the current level was less than 15 days worth of stock, and replenishment orders would not exceed 8 work day quantities. In other words, only 8 days worth of stock should be ordered for each replenishment (16). This guidance has been included in a recent revision to AFLCR 66-53, and reduces the authorized MIC stockage level of both expense and investment material to 15 days worth of stock (8:49). Also, MIC personnel are directed to "replenish the stock when it's half gone or earlier, if experience indicates additional order and ship time is required" (8:49).

This guidance has been interpreted in many different ways by the ALCs. One interpretation is that this guidance establishes a "7 days worth of stock" reorder point. Since a MIC replenishment order can be up to 8 days worth of stock, MIC personnel should conceivably only place a replenishment order at the "7 days worth of stock" level. However, MIC personnel can order material at any inventory level below 15 days worth of stock, as long as their total on-hand level does not exceed the 15-day level. For the purposes of this study and simulation experiments presented in Chapter III and IV, a 7 day reorder point, 15 day maximum stockage level policy was used. This policy will be referred to as the "15/7" inventory policy.

MIC Replenishment/In-Transit Delivery Time Policy. As noted earlier, the in-transit delivery time is the time it takes for MIC in-transit items to be gathered from the DS storage area, transported to the appropriate MA area, accepted through DS/MA receipt certification process, and finally added to the MIC inventory balance. McBride describes the process, after a replenishment issue request has been transmitted from the MA G402A system to the DS D033 (Stock Control and Distribution - Central Material Locator) data system, as:

> The D033 system transmits a notification to G402A when it sends a request to the appropriate warehouse for the picking and shipment of a part to MA. At the same time, an entry is added to the D033 suspense file for the in-transit item. When the MIC receives the part, it sends a notification back to D033 that clears the in-transit suspense. The G402A captures an image in its database of both the stock release notification from D033 and the response back from the MA MIC to clear the suspense. (22:39)

At the time of McBride's study, Depot Supply policy was that delivery from DS to MA for routine MIC replenishments should be accomplished as soon as possible, but not later than 12 to 24 working hours. At eight working hours per day, 24 working hours could equate to three full work days, or five full days if the delivery occurred in conjunction with a weekend (22:39). On 9 January 1989, this standard was reduced by the Headquarters AFLC Directorate of Distribution to a more stringent "not later than 12 working hours," or one and one-half work days in the USAF Supply Manual, AFM 67-1, *Volume III*, Part Two (11:21-10).

McBride collected a 30-day sample of in-transit lead times for a single MIC at Ogden ALC (OO-ALC) at Hill AFB, Utah. He determined that the in-transit time was distributed as a lognormal distribution with a mean of 5.46 days, and a standard deviation of 3.68 days using the Kolmogorov-Smirnov Goodness-of-Fit statistical test (22:55). He therefore concluded that the observed in-transit time exceeded the "12-24 working hour" standard directed in AFM 67-1, and that the length and variability of this time could have "significant impact on any attempt to assure high support while minimizing inventory levels in MA" (22:72).

Statement of Problem

This study examines the in-transit delivery time for replenishment of material in Depot Maintenance MICs from Depot Supply. A recent study found that a sample of in-transit delivery times for replenishment to Maintenance MICs from Supply were longer than the maximum allowable time frames established by policy (22:72). This effort investigates the actual in-transit delivery times experienced at Hill AFB, Utah (Ogden ALC), and the factors that affect this time. Also, this study evaluates the impacts of reducing the in-transit delivery time and its associated variability.

Research Questions

The following questions are proposed to investigate the problems stated above:

1. What are the current standards for in-transit delivery times of material to MICs from Depot Supply?

2. How have the current standards for the maximum allowable delivery times been established?

3. What actions are taken to determine if these standards are being met, and whether they are adequate, realistic, and accurately measured?

4. Can continuous process improvement opportunities to reduce the mean and variance of in-transit delivery time be identified by using Variance Reduction, Total Quality Control, and Statistical Process Control methods and techniques?

5. Can recent AFLC emphasis on involvement of all workers at all levels in the continuous improvement of all processes be applied to reduce the in-transit delivery times involved in the MIC replenishment process?

6. Using simulation of the Depot Maintenance environment, what are the impacts of varying in-transit delivery times upon material availability in the MICs?

Scope of Study

The general approach for analyzing actual in-transit delivery time involved collecting data that spans a six month period from 1 December 1988 to 31 May 1989. The population for this study includes six MICs that represent a broad cross section of end-item workloads at Ogden Air Logistics Center, Hill AFB, Utah. Additionally, this study adapts similar limitations in scope to McBride's effort. The main reason for many of these similarities is so that McBride's simulation methodology remains applicable to the current research questions.

There are, however, some notable expansions in scope that were pursued for this study. One expansion involves the types of items included in the research population of interest. McBride included in his effort lead time data on consumable assets (ERRC XB3 and XF3) issued by or through the

MIC in direct support to Depot Maintenance production activities and directly charged to an end-item. These items are considered direct material. Direct material normally becomes a part of the end-item which is undergoing maintenance. Direct material may be consumed in the maintenance production process, such as plating or painting, and is peculiar to the end-item being produced (8:5). McBride excluded indirect material from his analysis. Indirect material are those items that are costed as general overhead because they cannot be linked to a specific end-item or system (8:6). While the 15 day level stockage policy does not apply to indirect material, these items are assigned the same issue and delivery priorities as direct material. Therefore, the in-transit delivery time should not be significantly different for these two types of items. Also, the data collection method does not allow for stratification and separation of direct and indirect material in-transit data. For these reasons, this study includes both direct and indirect material in its population.

Additionally, this study includes both consumable and reparable items in its research population. McBride excluded ERRC XD2 and XF3 items that are reparable rather than consumable items from his study. At the time of his research effort, MIC stockage policies and formulas used to compute authorized inventory levels for reparable items differed considerably from policies and formulas used with consumable items. As noted earlier, a standard 15 day maximum stockage level now exists for any direct material item stocked in the MIC regardless of whether it is consumable or reparable. Thus, this study includes both consumable and reparable items in its population.

Finally, XB3 items maintained on bench stocks are excluded from this study since these assets are managed with different stockage policies. As noted by McBride, requests for bench stock items are perhaps more influenced by the frequency of bench stock reviews rather than actual usage experience. Also, production workers may adopt such practices as storing small quantities of parts in workbenches or tool chests. McBride asserts that these "two considerations would tend to distort and mask actual demand distribution for these parts (22:8)." Hence, analysis of the lead time involved in replenishing bench stock requests is outside the scope of this effort.

Organization of Thesis

Chapter I introduced this study by presenting the general issues, reviewing existing policy for MIC stockage and delivery times, stating the research problem, listing the research questions, and discussing the scope of this research effort.

Chapter II reviews literature and background information relevant to this study. Perspectives from civilian industry on the concepts of lead time and order cycle time are outlined. Both analytical and simulation models developed to study the effects of lead time uncertainty in inventory stockage policy are examined as well. Then, some ideas presented in a U.S. General Accounting Office (GAO) report on private sector inventory management practices are reviewed. Finally, some background discussion is presented on quality control programs and techniques that may be applicable for reducing in-transit delivery time.

Chapter III discusses the methodology used to address the research problem and the procedures used to collect and analyze the data on in-transit delivery time. Also, an outline of the simulation analysis experimental design is included.

Chapter IV presents and analyzes the results from data evaluation and in-transit delivery time simulation studies. Chapter V summarizes this study, and provides final conclusions and recommendations. Finally, extracts and examples of listings and programs used in data collection, simulation and analysis are included as appendixes to this study.

II. Review of Literature and Background

Overview

This chapter provides a review of the literature relevant to delivery time standards, and some background discussion on applicable Quality Control programs and techniques. First, definitions of lead time, and order cycle time are explained. Both of these terms, when referred to in the civilian context, relate to the in-transit delivery time for replenishment orders to the MIC. An illustration is presented that will show the possible impact that order cycle time may have on the amount of inventory that is held by an organization. Then, some analytical and simulation models that address uncertainty in lead time, and its effects on inventory stockage policy are examined. The advantages and disadvantages of analytical and simulation models are first discussed, followed by some of the significant research findings from these approaches. Next, some ideas presented by the GAO concerning private sector inventory management practices are discussed. The GAO provides a review of some of the general techniques and philosophies being used by civilian industry in the 1980's, including the just-in-time concept. Some background is then provided on recent emphasis given quality within the Air Force by exploring briefly the PACER IMPACT, AFLC QP4, and USAF R&M 2000 Variability Reduction Programs. Finally, a brief description of different quality control analysis tools that can be used to cause continuous process improvement by reducing in-transit delivery time concludes Chapter II.

Review of Private Sector Literature

Lead Time. Tersine, in his book Principles of Inventory and Materials Management, defines replenishment lead times as "the length of time between the decision to replenish an item and its actual addition to stock and can be constant or variable" (32:12). He further explains that probability distributions are used to describe variable lead time, just as they are in describing variable demand. Tersine breaks down lead time into the components displayed in Figure 1.

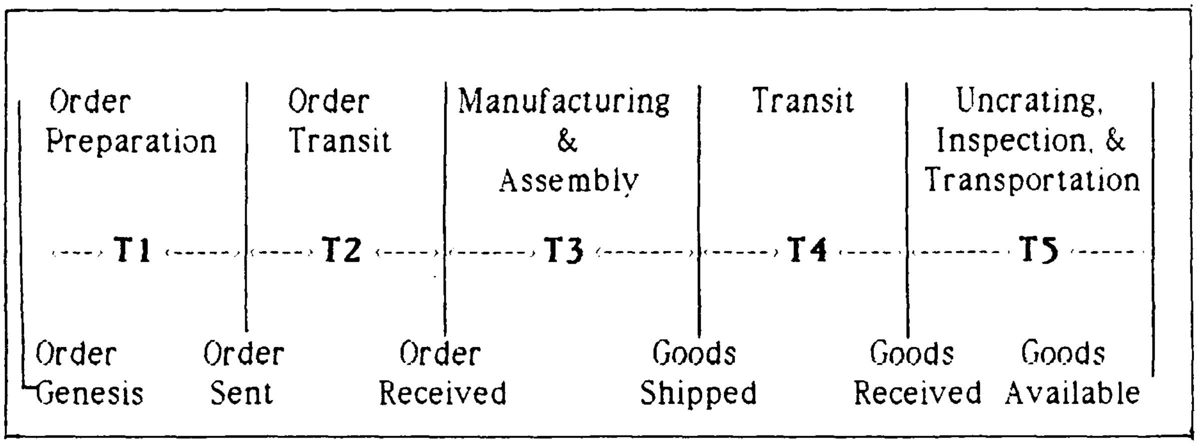

Figure 1. Major Components of Lead Time (32:12)

Tersine also notes that lead time can be expressed in simple mathematical terms as:

$$L = T1 + T2 + T3 + T4 + T5 = \text{Total Lead Time} \quad (1)$$

where

T1 = in-house order preparation time,

T2 = order transmittal time to supplier,

T3 = manufacture and assembly time,

T4 = goods transit time from supplier,

T5 = in-house goods preparation time (32:12-13).

The variables T2, T3, and T4 are influenced by factors outside the ordering organization, making them largely uncontrollable. However, according to Tersine, the variables T1 and T5 correspond to internal activities controllable by the ordering organization (32:12-13).

Variations in demand and lead time are two of the most prevalent areas where uncertainty enters into holding inventory. A common practice is to hold "Safety Stock," defined as:

> . . . extra inventory kept on hand as a cushion against stockouts due to random perturbations of nature or the environment. They are needed to cover the demand during the replenishment lead time in case actual demand exceeds expected demand, or the lead time exceeds the expected lead time. (32:184-185)

Holding safety stocks decreases the risk of stockouts, but increases holding costs (32:184-185). Basically, safety stock is held to protect against situations where the firm experiences a higher rate of demand than was forecasted or expected, or where the firm experiences a late delivery of goods. As the amount of safety stock held increases, the probability of a stockout decreases. An optimal safety stock level can be determined where the sum of safety stock holding costs plus the expected stockout cost is minimized (32:186). Recall from the earlier discussion in Chapter I on MIC stockage policies that there was no mention of safety stock being held in the MIC. MIC stockage policy itself does not contain a safety stock component in its computations. However, DS stockage policies incorporate a safety stock component into computing their stock levels, which compensates for demand and lead time uncertainty. Since DS stocks are held in part to provide replenishment for MIC requirements, safety stock held by DS provides indirect protection against stockouts in the MICs.

Tersine notes that reducing or shortening lead time can improve customer service, and reduce inventory costs. Lead time can best be reduced by shortening or eliminating those periods of time where orders are inactive. He asserts that reducing lead time "can provide an enormous competitive edge through lower costs and faster responses" (32:400). In relating this concept to material held in the MICs, consider the following: If material is not available in the MICs to support depot maintenance, a work stoppage may occur. The time spent waiting for receipt of material not on hand in the MIC represents an "inactive" time for aircraft and components undergoing repair. Having material on hand in the MIC when needed would enable MA to eliminate the additional lead time caused by material shortages.

While the costs associated with work stoppages in Depot Maintenance due to material shortages are difficult to quantify, it is hard to deny that these costs do accrue and are significant. In the case of an aircraft undergoing depot maintenance, a material shortage may only cause a minor rescheduling action or a mechanic work-around. The worst case scenario, however, is where a material shortage could delay returning an aircraft to an operational unit. In the case of spare components undergoing depot repair, a material shortage may only delay the spare from going "back on the shelf" for subsequent issue. More critically, however, a material shortage may delay the repair of a component required to fill an urgent requirement at an operational unit. In all the above scenarios, mission readiness suffers.

<u>Order Cycle Time</u>. Stock and Lambert, in <u>Strategic Logistics Management</u>, provide additional interesting perspectives on delivery time issues from private industry. They examine the concept of "order cycle

time" and the various time components that sum up to be the total lead time involved with getting products to the customer, or end-users. They use the term "customer order cycle" to represent replenishment lead time, and break this time down into components similar to Tersine's approach outlined above. Their customer order cycle includes all time that has elapsed from the customer placing the order until the product is received and placed into the customer's inventory. They list the following components of a typical order cycle: 1) order preparation and transmittal; 2) order receipt and order entry; 3) order processing; 4) warehouse picking and packing; 5) order transportation; and 6) customer delivery and unloading (31:499). Stock and Lambert assert that many firms take a too limited view of the order cycle time, considering only the "controllable" segments of the cycle that are internal to the organization. For instance, many firms only evaluate the elapsed time from receipt of the customer order until the order is shipped to the customer. According to Stock and Lambert, this limited viewpoint may cause a firm to miss opportunities to reduce the total order cycle time (31:500). A holistic, broad-based viewpoint may yield opportunities to provide better customer service, thus incurring a competitive advantage.

The Impact of Order Cycle Time. Stock and Lambert cite a study sponsored by the National Council of Physical Distribution Management that asserts the largest portion of the total order cycle time for manufacturers occurs between the time the order has been shipped until the time it is received. The average total order cycle time for all manufacturers studied was 10.3 days. Within this average total order cycle time, 4.1 days represented the average shipping time to the customer (31:500). Another concern addressed by these authors was the issue of order cycle time variability or consistency. They offer an example (Figure 2) that illustrates the variability that might occur in each component of the total order cycle time. They base their example on the normal probability distribution, but other theoretical distributions may actually be more appropriate. In their illustration, the actual order cycle ranges from 5 to 25 days. Stock and Lambert assert that variability is expensive to the end user or customer because he will carry safety stock to cover for possible delays in delivery. The alternatives are stockouts and/or work stoppage situations. Stock and Lambert offer the following scenario to explain why order cycle consistency (reduced variability) is more preferable to the customer than fast delivery:

> If the average order cycle time is 15 days but can be as long as 25 days, the customer must maintain additional inventory equivalent to 10 days' sales just to cover variability in lead time. If daily sales equal 20 units and the company's economic order quantity is 200 units--a 10-day supply--the average cycle stock is 100 units--one half the order quantity. The additional inventory required to cover the order cycle variability of 10 days is 200 units. Excluding demand uncertainty, average inventory will increase from 100 units to 300 units due to the variability in the order cycle.
>
> Which has the greatest impact on the customer's inventory--a five-day reduction in the order cycle, or a five-day reduction in order cycle variability? If the customer continued to order the economic order quantity of 200 units, a five-day reduction in the order cycle would result in little or no change in inventories. The customer would simply wait five days longer before placing an order. On the other hand, if the customer ordered 100 units every time instead of 200, the average cycle stock would be 50 units rather than 100 units, but safety stock of 200 units would be required to cover the 10 days of variability. The result would be a reduction in total average inventory of 50 units, from 300 to 250 units. However,

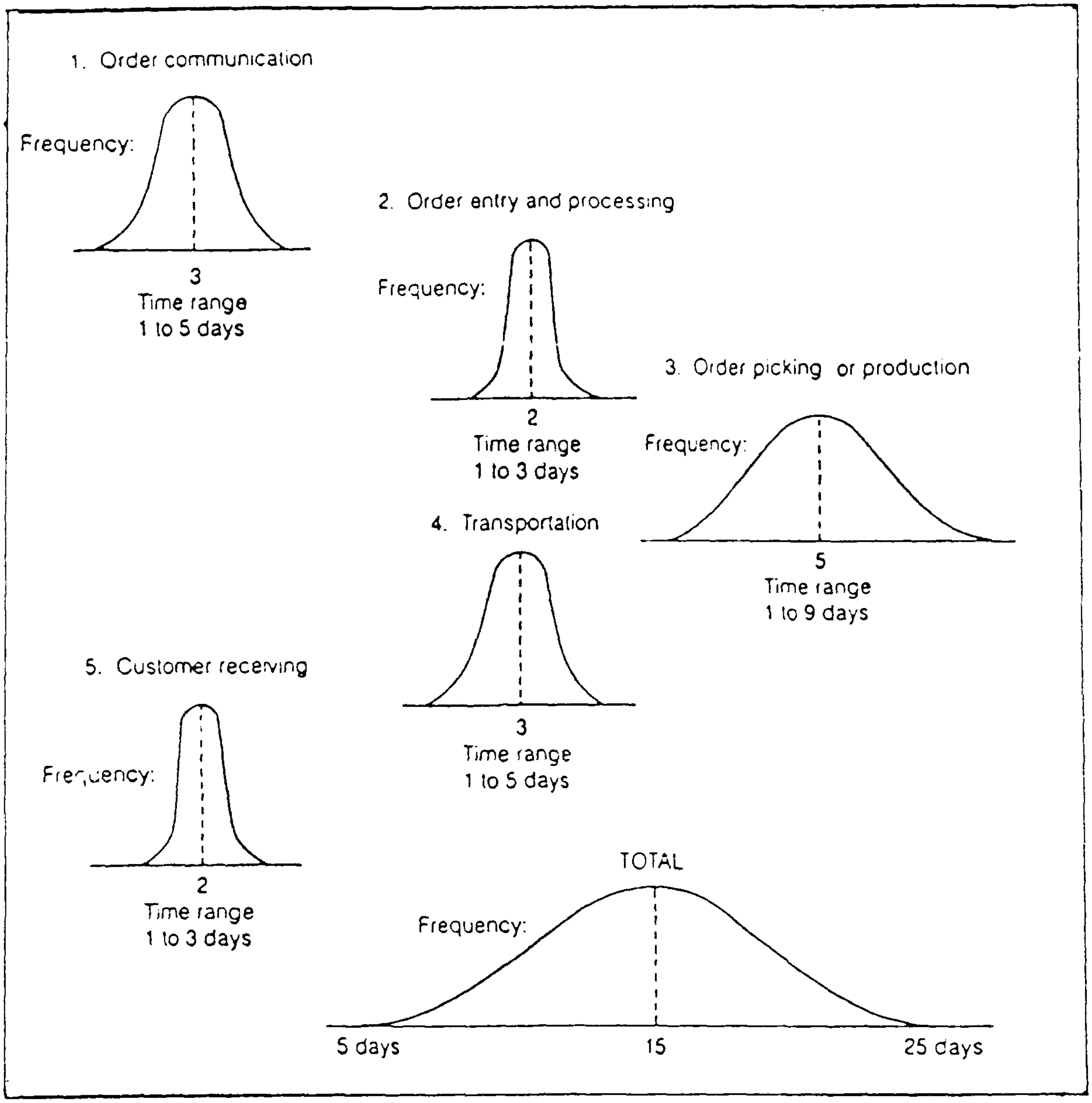

Figure 2. Total Order Cycle Time with Variability (Reprinted from 31:501)

> a five-day reduction in order cycle variability would reduce safety stocks by 100 units and result in an average inventory of 200 units. (31:501-502)

To relate this concept of reduced variability in order cycle time back to MIC stockage policy, uncertainty in lead time is even more critical, considering no safety stock is held in the MIC. A relatively certain order cycle time would ensure that "15 days worth" of stock would provide adequate support to MIC material requirements for that period of time. However, as noted earlier in Chapter I, McBride's study found that in-transit delivery times may be far greater than the "12-hour" standard per AFM 67-1, with a 3.68 day standard deviation, which may be viewed as highly variable (22:55, 72). Reducing the lead time and its associated variability would allow recently reduced maximum stock levels to provide improved levels of material support to depot maintenance organizations.

Comparison of Analytical Versus Simulation Models. There are two broad categories of methods useful for analyzing the impact of lead time modification: analytical models and simulation models. Analytical models express a phenomenon of interest in mathematical terms and formulas. In the case of analytical inventory models, the objective usually is to provide the maximum level of support, with cost held to a minimum. Some analytical models can determine the "optimal" level of stock that will provide the maximum level of support and minimal cost. However, lead time unreliability is often not adequately considered in inventory theory because incorporating lead time unreliability into analytical cost-minimization models makes these models extremely cumbersome to work with. Vinson has noted three reasons why lead time uncertainty is hard to consider analytically. First, lead time may not be independent of the pattern of demand (e. g., "a stackup of orders may occur at the factory, or a large order may take longer to deliver than a small order") (35:88). Second, variation in lead time may not fit familiar probability distributions, or may shift around in no discernable pattern. Third, successive lead times may not be independent of each other. For example, this could happen if orders are received and processed in sequence and thus, if one order is delayed, others will also be delayed. Vinson concluded that a way around the "theoretical difficulty of incorporating lead time unreliability in inventory decision-making is through the construction of inventory simulators " (35:88).

Gross and Soriano have asserted that while a variety of analytical models have been developed, their applicability to problems with stochastic demand and lead time are "limited to some special cases" (12:B-61). Their study focused on an (s, S) periodic review inventory policy where s is the reorder point and S is the recommended stockage level. In their work entitled "The Effect of Reducing Leadtime on Inventory Levels - Simulation Analysis," they stated:

> For greater flexibility and reality, a simulation approach was decided upon. As a by-product, generalization as to the effect of various parameters influencing allowable inventory reductions for decreases in mean leadtime for any s, S periodic policy were available. An empirical scheme, based on the simulation results, is also indicated which can be used to readily yield approximations of the allowable reductions in safety levels and accompanying on-hand inventory level, resulting from changes in mean leadtime as well as in the variance of demand and leadtime, for a given system performance. (12:B-61 to B-62)

Nahmias went as far as to say that with the inclusion of set-up cost, random lead times and/or partial backordering in models, analytically determining the optimal inventory policy may not even be possible. Nahmias also noted, however, that a simulation approach "provides a means of determining the best policy from a given class when analytical solutions are difficult to obtain" (25:919).

Bagchi and others, in their article "The Effect of Lead-Time Variability: The Case of Independent Demand," outlined a classification of research using simulation techniques in modeling inventory systems which was first developed by Banks and Malave. The authors listed six categories as noted below:

1. Analytic solution impossible or analytic solution extremely complex.
2. Comparison of models.
3. Verification of analytic solutions.
4. Variance reduction techniques.
5. Model validation and verification.
6. Optimization techniques. (1:169)

Bagchi and others note, therefore, that the use of simulation in inventory modeling has "touched every facet of inventory theory" (1:169). They claim that given the ability to generate random demands and given the initial conditions of the system, the modeler can easily simulate an inventory system. Once the simulation has been formulated, and has been determined to be a valid representation of the inventory system, it is easy to estimate the attributes of interest. Bagchi and others also assert that "simulations offer insight that may not be readily gleaned from direct mathematical analysis" (1:169).

Analytical Model. Kaplan, in his article " A Dynamic Inventory Model with Stochastic Lead Times," presented optimal policies for a dynamic inventory problem when the time lag in delivery of an item is a discrete random variable with known distributions. It is a cost-minimization model that computes optimal inventory levels subject to ordering, holding, and shortage costs (19:491). One significant finding from Kaplan's use of the model was that while holding other parameters constant, an increase in the maximum possible delivery time lag, or lead time, increases the optimal average inventory level (19:504).

Simulation Models. Gross and Soriano developed a simulation model for a periodic review (s,S) inventory policy with both demands and lead time being stochastic. The model was built to represent a military supply system, where the lead time reduction might be achieved by using airlift rather than sealift for resupply. The model operated as follows:

> Once every period r, to be referred to as the review period, the program calls for a review of the inventory position, i.e., on-hand plus on-order inventory level. If the inventory position is below a level s, an order for the amount which will bring the inventory position back to a level S is placed. (12:B-61 to B-62)

Demand per period was established as having either a Poisson or normal distribution. Lead time was assumed to be either normal, uniform or exponentially distributed, or deterministic (12:B-62). The purposes of their study were to examine the effect of reducing lead time on safety stock levels required to maintain given customer service goals, and to study parameter sensitivity. They found that:

1. Reducing lead time from 13 weeks (if sealift was used), to two weeks (if airlift was used) results in a a reduction of about three weeks of supply in safety stock, which in turn results in an "average on-shelf inventory reduction" of about three weeks worth of stock.

2. The mean and variation of lead time appear to be the most sensitive input parameters to the model. Less sensitivity was noted in the case of variation in demand and in the distribution shape of demand (12: B-74 to B-75).

Vinson designed a simulation model to evaluate different combinations of stockout cost, demand variability, mean lead time, and lead time variability on changes in optimum safety stock and total inventory cost (35:87). More that 250 different hypothetical inventory items were examined. Vinson found that the cost of ignoring lead time unreliability could be extremely high, and that unreliability in lead time is "often a more dominant factor than demand variability in minimizing inventory costs" (35:94). If all other variables remained constant, Vinson found that given a particular mean lead time, as the variability of the lead time increased, the optimum safety stock required increased significantly. In some cases, the increase in optimum safety stock was six-fold (35:94-95). Vinson also noted that "lead time unreliability is the dominant source of stockout cost. Only when lead time is highly reliable and/or when mean lead time is quite long or variability of demand unusually severe does demand variability become the dominant factor" (35:97).

Nahmias used a combined approach of developing an inventory approximation model with simulation used as an evaluating tool. His dynamic lead time lost sales model assumes that unsatisfied customer demand will be either completely or partially lost rather than backordered. Nahmias' model is a periodic review (s, S) policy that considers ordering and set-up costs, and partial backorder situations. He developed analytical models that provided approximately optimal inventory policies which minimized cost. He then compared the analytic approximations of optimal inventory policies to simulated results with maximum lead times ranging from five to 20 periods, and with a variety of configurations of cost structure, demand and lead time distributions (25:904-905). The resulting optimal simulated solutions were then compared in terms of expected costs per period to solutions found by using approximation methods. One major finding was that for larger lead time periods, the error in the approximation policies relative to the simulated policies increased. Another interesting finding was that deterministic lead times tended to have a higher amount of error than other lead time distributions, with geometrically distributed lead times resulting in the lowest error. Nahmias attributes this to the fact that geometric distributions tend to put the greatest weight on smaller values of lead time. Smaller values of lead time result in lower approximation error (25:920).

Bagchi and others used a combined analytical and simulation approach in their work, "The Effect of Lead-Time Variability: The Case of Independent Demand," to evaluate the impact on stockouts and stockout risk if the variability of lead time is ignored. The authors also examined a case study that was conducted for the Air Force by Jack Hayya in 1980. The purpose of Hayya's study was to see whether lead time variability had any significant impact on inventory support and planning in AFLC. At the time, AFLC managed a consumable inventory of over $2 billion, with an annual procurement of nearly $1 billion (1:160). The authors explained the AFLC inventory policy as it then existed as:

> AFLC used a continuous review (R,Q) model, in which R is the reorder point and Q the order quantity. The determination of safety levels and order quantities was primarily constrained by appropriations. Subject to this constraint, R and Q were calculated to minimize the number of backorders and shortages of essentiality-weighted items. The solution was obtained by the method of Lagrangian multipliers, using the assumption that the upper tail of the distribution of demand during lead time is Laplace, that is, exponential. Experts agree that such problems

can be easily solved, provided that the number of items is relatively small. But such solution techniques become computationally and economically infeasible for a larger number of items, and AFLC had 500,000 of them. (1:160)

According to the authors, the major finding of Hayya's study was that lead time variability did exist and should be considered in AFLC inventory policy. If AFLC included lead time variability in their computations, more investment in safety stock would be required if all else remained equal. However, it was also found that shifting demand patterns combined with lead time variability do impact DS stock levels dramatically. The authors conclude that AFLC could have cut the number of backorders in half by including lead time variability in their computations at the expense of larger order quantities (1:162).

Another interesting finding of Bagchi and others in their examination of Hayya's study was that lead time data for 60 different items followed many common distributions. The Kolmogorov-Smirnov Goodness-of-Fit test was used with samples varying in size from 30 to 100 to fit procurement lead time to the lognormal, gamma, normal and Weibull distributions. All of these distributions fit the data very well, with the gamma distribution being the overall best fit. The authors assert that the gamma distribution has "often been postulated as being a good characterization for the distribution of lead time, and our results supported this assumption" (1:160). It should be noted that the lead time data studied in the above efforts in many cases were expressed in terms of weeks or months. When studying on-base in-transit delivery times, the time units involved are in terms of days and hours. For this reason, the above findings are most useful for comparative purposes.

The authors also provided a table of what they termed "the state of the art" in applying theoretical probability distributions to demand per unit time, lead time, and demand during lead time which is shown in part in Table 1. The distinction between "fast-moving" and "slow-moving items" is left up to the analyst's judgement. "Lumpy demand" is demand that is occurs in "lumps" or "batches" in contrast to demand that occurs at a steady, continuous rate (1:169).

Table 1: Synopsis of the State of the Art in Fitting Theoretical Distributions to Demand and Lead Time Data (1:170)

Demand Characteristics	Demand per Unit of Time	Lead Time	Demand During Lead time
Fast-Moving Items	Normal	Gamma	Gamma Approximation
	Normal	Exponential	Truncated Exponential
	Exponential	Geometric	Exponential
Slow-Moving Items With Lumpy Unit Demand	Stuttering Poisson	Gamma	GPG Distribution
	Stuttering Poisson	Normal	GPN Distribution
Slow-Moving Items With Unit Demand Not Lumpy	Poisson	Normal	Hermite
	Poisson	Gamma	Negative Binomial
	Poisson	Exponential	Geometric
	Negative Binomial	Gamma	LPG Distribution

Notes: 1) The GPG distribution stands for geometric order size, Poisson customer arrivals, and gamma lead time; 2) The GPN distribution stands for geometric order size, Poisson customer arrivals, and normal lead time, and 3) The LPG distribution stands for logarithmic order size, Poisson customer arrivals, and gamma lead time.

Intermediate Summary

An interim summary of the private sector literature concerning the concepts of lead time, and the order cycle time required for inventory replenishment is appropriate at this point. The various components of lead time and order cycle time were reviewed. Lead time as defined by Tersine is the time between the decision to order or replenish an item and its actual addition to stock. Tersine includes the time required to manufacture and assemble the items ordered by the customer in his definition of lead time. Order cycle time as defined by Stock and Lambert is the time elapsed from order placement until an items is placed into the customer's inventory. Stock and Lambert do not include manufacturing and assembly time in their definition of order cycle time. For practical purposes, however, lead time and order cycle time are synonymous terms. The views of Stock, Lambert and Tersine are similar in that they all assert that reducing lead time (or order cycle time) values and their associated variability can result in significantly better and more consistent support of customer requirements. Reduced inventory levels and safety stock requirements need to be held to prevent stockouts and work stoppages in an environment where lead time and order cycle time is less variable and more consistent. It was noted that in the MIC stockage environment, where no safety stock is held in the MIC, reducing the in-transit delivery time and its associated variability would enable the recently reduced "15 days worth of stock" inventory levels to provide improved levels of material support to depot maintenance organizations.

Another major topic presented in this section of Chapter II was a description of various analytical and simulation models devised to address uncertainty in lead time, and its effects on inventory stockage policy. First, the literature showed that analytical models are extremely cumbersome to work with when lead time unreliability is included in their computations, and also limited to special applications. Also, determining the "optimal" level of stock that provides the maximum level of support at minimum cost may not even be feasible using analytical models. Inventory simulation models, on the other hand, have found widespread use and application in examining the effects of lead time variability on stockage performance.

For the analytical models reviewed, increased lead time usually resulted in a higher average inventory level requirement to maximize customer service and minimize costs. For the simulation models investigated, the mean and variance of lead time were found to be two of the most sensitive parameters in simulation experiments. Reduced lead time usually resulted in lower levels of inventory and less safety stock being required to achieve customer service goals. Variability of lead time was often a more dominant factor in minimizing inventory costs than variability in demand. Finally, lead time data was found to "fit" several different probability distributions (Table 1), with the gamma distribution often providing the best overall characterization of lead time data. However, studies cited in this chapter focused on "procurement lead time," or time elapsed between order and receipt of material from geographically separated customers and suppliers. Direct application of the results of these studies to on-base in-transit delivery time may not be fully warranted. Additionally, as noted by Vinson, variation in lead time may not fit familiar probability distributions, or may shift around in no discernable pattern (35:88).

In the next section, some of the more progressive private sector practices and views on inventory management are examined in a review of a GAO report on inventory management practices in industry today. Whether these practices can be applied by the military services is also explored.

Review of GAO Report on Private Sector Inventory Management Practices

The GAO published a study in July 1988 that identified practices used in the private sector to manage and improve control of inventory. Additionally, the GAO sought to determine whether the practices they identified were applicable for use within the DoD (34:25). The GAO noted that the Secretary of Defense has encouraged the military services to explore the private sector for inventory management techniques and concepts, and that "such interaction is a step in the right direction" (34:2-3). The GAO also acknowledged that there are basic differences between the private sector and the DoD in their respective inventory management practices, and reasons for holding inventory (34:2). The GAO explains these differences as:

> The military services hold inventory to support missions with no-fail objectives. Thus, the military perspective is the more inventory DoD has, the more sustained military capability it has--i.e., with more safety stock, it will be better able to meet its no-fail objective. The private sector holds inventory in support of future sales with a profit objective. Since inventories can also be a drain on profits, the seven companies we visited have established goals for reducing inventories to a minimum and eliminating safety stocks to improve profits. (34:2)

However, the GAO asserts that the military services can still improve inventory management within the DoD by applying private sector concepts and procedures (34:2).

Seven companies were included in the GAO study, six of which held inventory in excess of $1 billion, with the seventh company approaching $1 billion in inventory holdings. The companies were: Caterpillar Corporation; General Electric Company; General Motors Corporation; Hewlett-Packard; J. C. Penny Company; Sears, Roebuck and Company; and the Westinghouse Electric Corporation (34:25).

The GAO found that views on inventory management have undergone significant changes in the 1980's. Companies are attempting to reduce their overall investment in inventory, while at the same time maintaining or improving levels of sales and customer support. In fact, many top executives from the companies examined have set corporate goals to reduce inventory significantly (34:1). To meet reduced inventory goals while maintaining or improving customer support, the companies examined have adopted just-in-time techniques. The GAO defines the just-in-time concept as:

> This concept calls for the production and delivery of the right material, at the right quality level, in the right quantity, at the right time, and to the right place, using a minimum of facilities, equipment, materials and human resources. Just-in-time requires substantial reduction in set up times, improved material flow, and improved quality. (34:6)

According to the GAO report, minimum inventory is implied by the just-in-time concept. An item reaches the point of consumption or use "just in time, but not before it is needed" (34:6). While all elements of the just-in-time philosophy have not been fully adopted by the seven companies surveyed, inventory reduction and improved product quality have found widespread acceptance. In short, excessive inventory levels are believed to hide operational inefficiency. The increased carrying costs associated with excessive inventory levels is seen as a drain on current and future profits by those companies examined by the GAO (34:6).

To meet inventory reduction goals while maintaining customer service levels, the GAO noted that the companies were using three general techniques: 1) simplify inventory handling and decision-making processes; 2) automate processes where possible, appropriate and cost-effective; and 3) integrate processes between the company, suppliers, carriers and customers, as well as "internal customers" within the company itself (34:12). Many companies emphasize studying the physical movement of inventory to eliminate unnecessary steps (34:12). Also, simplification should be pursued before automation. In many cases, "automation is not a cure for inefficient operations, but rather mirrors operations whether they are efficient or inefficient" (34:12).

Five of the seven companies pursued "continuous process improvement" as a philosophy in day-to-day operations. Under this philosophy, all major functions within a firm (including inventory management), should be continuously improved with perfection being the ultimate goal (34:8). As part of the "continuous improvement" process, all the companies measure and assess the performance of individuals and groups on a regular basis. "It is this type of performance measurement and exception management that brings discipline to the operating environment," asserts the GAO report (34:18).

Among the performance measures used by the companies to assess the flow of inventory were order fill rates and "dock-to-stock time" (34:18). The order fill rate is the number of orders filled expressed as a percentage of the total number of orders. Most of the organizations reported having fill rates above 90%, with the range running from 78 to over 90% (34:18). "Dock-to-stock" time was defined as "the amount of time it takes to receive incoming material, count and inspect the material, and move it to its storage location"(34:18). The companies surveyed reported an average 1 day dock-to-stock time, with some companies reporting this time in terms of hours. Use of bar coding, and computer terminals on receiving docks, as well as scheduled deliveries were noted as processes that allowed for reduced dock-to-stock times (34:18).

The companies noted in the GAO report have industrial inventory systems that are very comparable to those within AFLC. The next section of this chapter discusses some of the continuous improvement programs on-going and in development within AFLC and the Air Force as a whole. Also, a brief overview of applicable Quality Control analysis tools that could aid in continuously improving the process of in-transit delivery of replenishment assets to the MICs is provided.

Background on Applicable Quality Control Programs and Techniques

PACER IMPACT and the AFLC QP4 Program. The AFLC maintenance community is a wide-ranging and complex environment. It is responsible for the maintenance, repair and modification of aircraft, missiles, aircraft engines, and most of the components of these weapons systems. Nearly 36,580 persons are involved in AFLC's maintenance operations at five Air Logistics Centers and two specialized repair facilities. In 1988, the budget for depot maintenance activities within AFLC approached $2.2 billion. During that same year, AFLC depot maintenance activities repaired or modified over 865 aircraft, 6383 engines, engine modules and gas turbine engines, and 836,642 other weapon system components (15). With this level of ongoing activity, certainly productivity should be a continual concern. PACER IMPACT is an AFLC program to improve productivity in the above depot maintenance activities. The major principles of PACER IMPACT include:

1. Application of new technology.
2. Development and implementation of innovative and effective methods improvements.
3. Enhanced productivity through a focus on environmental concerns as they relate to industrial processes.
4. Improved management and control of material assets.
5. Continued employee development and motivation. (15)

Brigadier General John M. Nowak, former Deputy Chief of Staff for Maintenance at Headquarters AFLC, had the following to say concerning PACER IMPACT:

> With the President's focus on productivity and unit cost, PACER IMPACT, the Depot Maintenance Productivity Program, is more crucial than at anytime before. The search for greater productivity improvement crosses all boundaries; government, industry and academia. It encompasses improvements in technology, people programs, processes, quality, environment, material control and data systems. If we are to do better, to use less and constantly improve then there must be a free flow of information into the [Air Logistics] centers and between the centers. Any vestiges of business as usual must be replaced with a desire to innovate and experiment. PACER IMPACT provides a climate where we can innovate, we can experiment, we can do better. (5:ii)

General Nowak went on to note some of the examples where AFLC "did it better" in FY 88 (5:ii). The most prominent example was in the area of continuous quality improvement. The AFLC "total Maintenance concept, designated QP4 (Quality is People, Process, Performance, and Product), emphasizes continuous worker participation in the improvement of processes" (5:ii). According to General Nowak, QP4 has revolutionized AFLC's approach to building quality into every facet of their business, and has allowed them "to provide combat strength through quality logistics: a quality-equipped and 100% satisfied customer in the field" (5:ii).

QP4 was primarily developed in response to the desires of General Alfred G. Hansen, the Commander of AFLC, for a total quality management system in AFLC (5:12). The core mechanism of QP4 is the Process Action Team (PAT), which:

> . . . are small groups of workers and staff personnel who are most closely associated with a maintenance process. They are trained in quality productivity improvement, philosophy and analytical techniques so they can systematically improve their assigned process. PATs use such sophisticated techniques as PARETO Analysis, Statistical Quality Control and cause and effect relationships to learn about and improve their process but their real value is their knowledge of the process gained by intimate association over a period of time. PATs are not restricted to industrial processes, but include administrative and staff processes as well. Implementation of QP4 has progressed rapidly and is already showing impressive results. By the end of FY 88 there were well over 100 PATs working throughout AFLC/MA. Training on QP4 is widespread and will continue to expand to cement the quality cultural change needed for effective continuous process improvement. (5:12)

According to AFLC Pamphlet 66-65, the QP4 program is the accumulation of years of transition "from a reactive quality control program to a prevention oriented continuous process improvement total quality system" (5:11). Getting all personnel involved in striving for improved quality and continuous process improvement through education and PAT activity is the basic thrust of QP4. QP4 is designed to be a total system aimed at continually "improving and optimizing AFLC maintenance processes and working with other organizations on those processes that cross functional lines" (5:12).

USAF R&M 2000 Variability Reduction Program. The R&M 2000 Variability Reduction Program (VRP) was developed to improve the reliability and maintainability (R&M) of Air Force systems. Poor designs and manufacturing processes result in unreliable and difficult to maintain equipment that contribute to high support and acquisition costs. The overall strategy behind VRP is to nurture within the Air Force and the defense industry a concept of excellence in design and manufacturing (17:1). The basic tenets underlying the VRP include:

1. Commitment of top-level managers and commanders
2. Involvement of people at all organizational levels
3. Application of proven, cost-effective VRP techniques and technology in an orderly, systematic manner
4. Encouragement of continual variability reduction, or continuous process improvement. (17:1)

The R&M 2000 VRP emphasizes high reliability, improved design concepts, and highly capable manufacturing processes in developing, acquiring and supporting Air Force systems. A reliable product meets the requirements of the customer and functions over its useful life with no variation. A well-designed product is insensitive to physical and functional variation due to environmental conditions, manufacturing processes, or operational use in the field. Finally, a highly capable manufacturing process pr duces uniform, defect-free items that do not vary from design specifications (9:1).

The first step is usually to define customer requirements. Customer requirements (or "performance-over-time" requirements) that are translated into design and manufacturing specifications should be thought of as "Target Values," or "the best values for reliable performance in the user's operational environment" (5:1). Improved performance at lowered costs can result from reducing variability around the target value. Waste in manufacturing operations, systems support, and service use will also decrease (9:1). The notion of reducing variability is graphically illustrated by Figure 3. Also, recall the earlier discussion in this chapter of Stock and Lambert's ideas on reduced order cycle time variability. Reducing the variability of order cycle time, which is similar to the in-transit delivery time for MIC replenishments, is desirable in order to reduce uncertainty and avoid work stoppages due to lack of material.

Three tools useful in variance reduction are: 1) Statistical Process Control (SPC); 2) Taguchi Methods; and 3) Quality Function Deployment (QFD). The primary difference between these methods is in their target application areas. SPC is a method that is used for "on-line," existing systems. Taguchi methods, on the other hand, are more applicable to production and design operations. A third method, QFD, considered an "off-line" method for the design of new products and processes (17:2). Lieutenant Colonel Hull defines SPC in his memorandum "R&M Variability Reduction Program" as:

> . . . an on-line technique for reducing variability in manufacturing and assembly processes. The capability of production processes to produce increasingly more uniform, defect-free products is improved by continually identifying and eliminating random causes of variability. The control chart

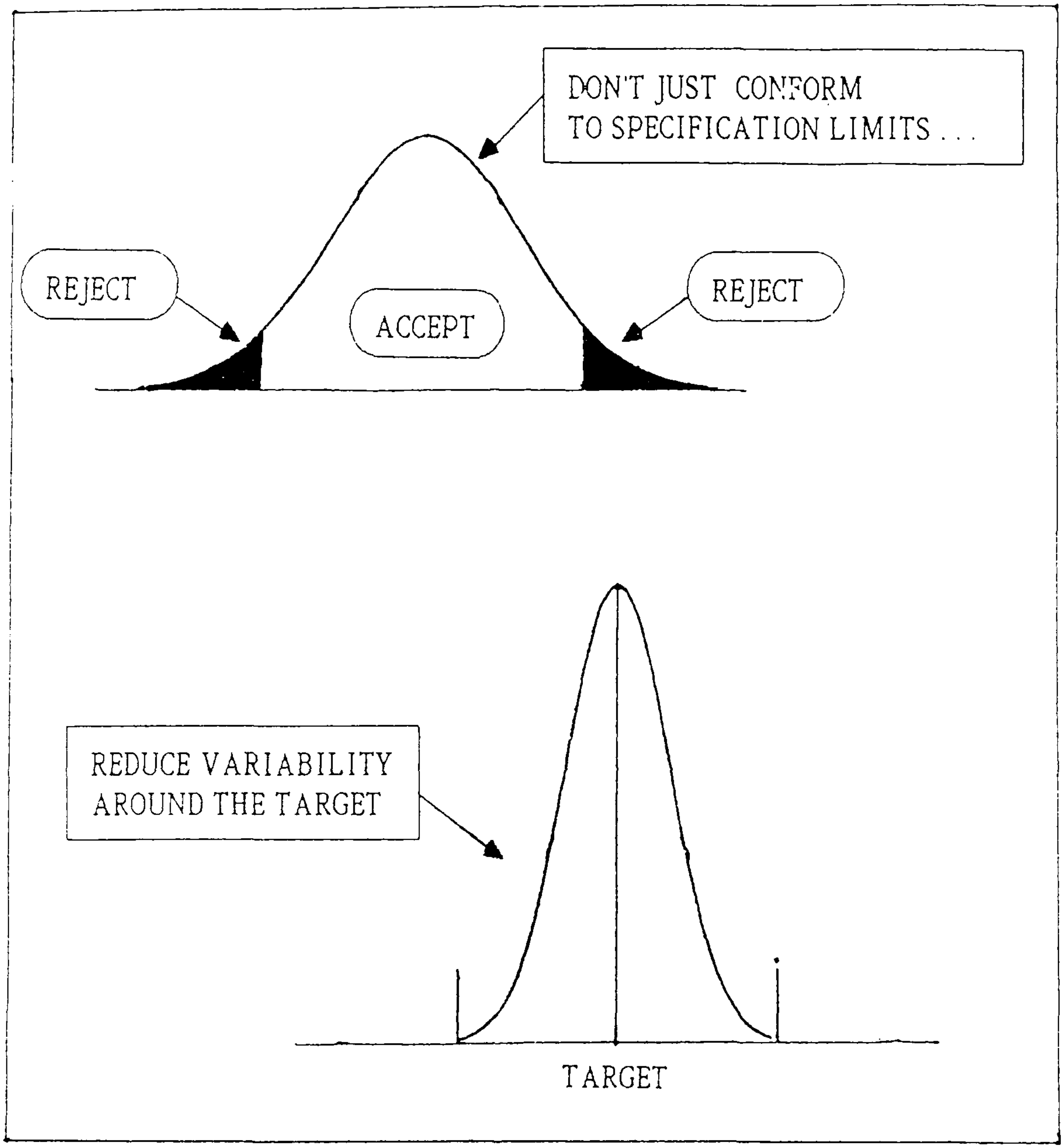

Figure 3. Reducing Variability Around the Target Value (Adapted from 9:2)

> helps differentiate assignable causes of variability from random causes. (17:2)

Workers use control charts to eliminate assignable causes of variation and keep processes under statistical control (17:2).

Taguchi methods are another set of techniques discussed by Hull that are used to improve the capability of manufacturing operations and to design reliable products. Taguchi was a noted Japanese quality control authority. His basic premise is that design and manufacturing excellence are directly related with cost reductions. That is, the best design is one that causes the lowest monetary loss in design, production, and use (12:2). According to Hull, the essence of this method is parameter design selection:

> Taguchi uses efficient experimental design techniques to select the design parameters settings that make products and processes robust (insensitive to the effects of uncontrollable sources of variability such as the environment and deterioration in use). Scores of design variables can be analyzed simultaneously to select the best design and production process. (17:2)

Another VRP technique presented by Hull is QFD. The primary aim of QFD is to ensure that customer requirements, or target values, drive the product design and production process. The full benefits of VRP tools and techniques cannot by realized unless the customer's target values are clearly defined, and everyone involved with the process is mobilized to reduce variability around the target value (17:2).

Hull summarizes the three primary USAF R&M 2000 variance reduction tools, explaining their interaction and relationships as:

> QFD is a systems approach for translating users' requirements into product and process characteristics and deploying their requirements throughout the company. QFD identifies the critical design characteristics for which Taguchi methods may be employed, and the critical manufacturing processes which should be controlled by SPC or other on-line techniques. (17:2)

Review of Quality Control Analysis Tools. Meredith describes some techniques and tools that may be used by a PAT team to analyze problems (Figure 4). These techniques include:

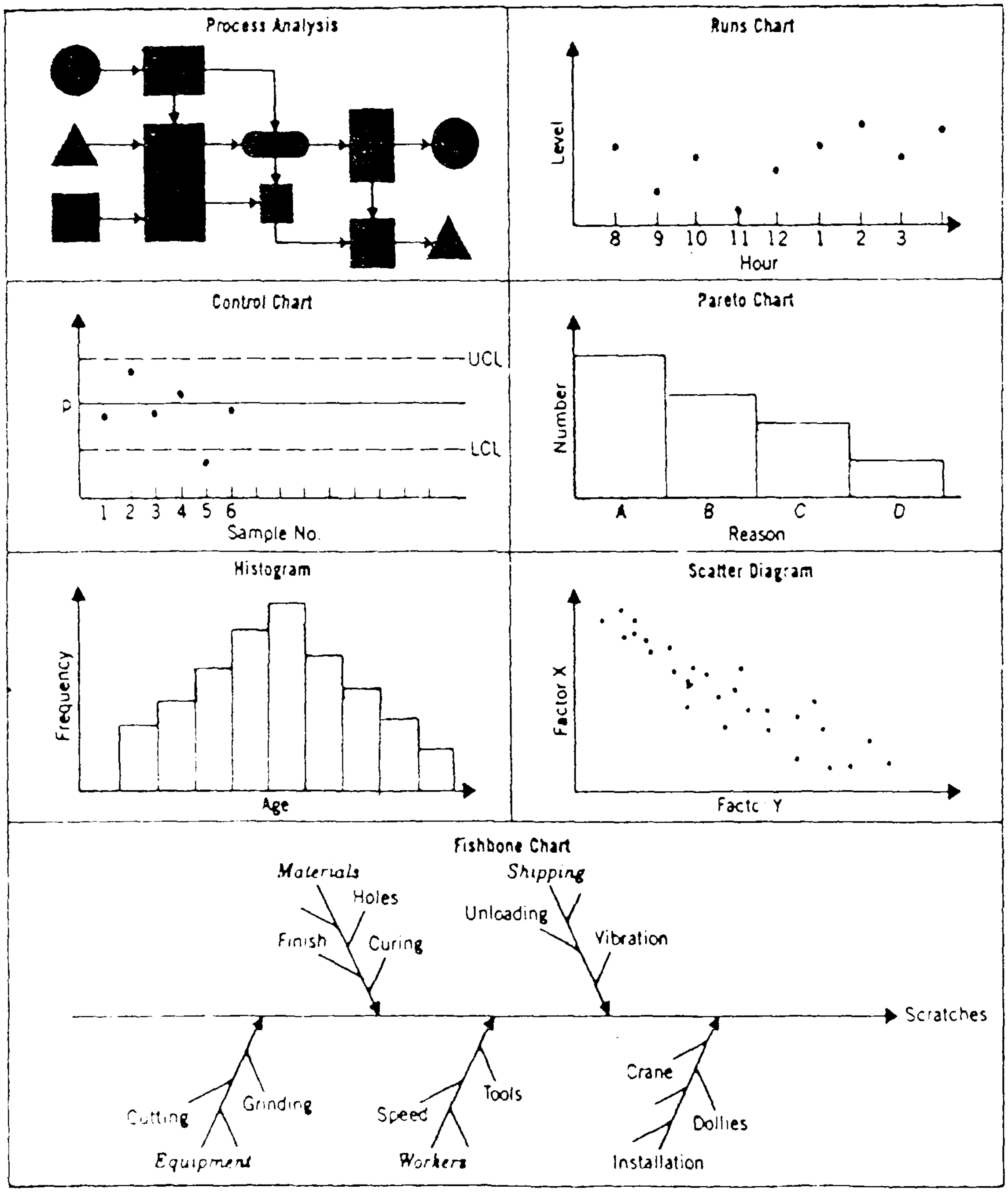

Figure 4. Quality Control Tools (Reprinted from 23:550)

1. Process analysis chart: This is a flow chart of how a system or process works showing the inputs, operations and outputs of the process. By displaying the process visually, workers can often spot the source of a problem, or identify where and what more information is needed to solve the problem (23:549).

2. "Runs" chart: This graph shows how a variable has changed over time. By analyzing the data points, the members of a work team such as a PAT can determine if the process is performing as it is supposed to perform. There may be excessive variation in the data, a disturbing trend, or random unacceptable points that can be spotted by members of the work team (23:549).

3. Control chart: This chart enables a work group to "distinguish between chance variation in a system and variation caused by the system being 'out of control,' called assignable variation" (23:524) When a process goes out of control, it must first be detected, then the assignable cause located, and finally, the appropriate control action or adjustment made (23:524). By putting upper and lower control limits on the chart of sample data, the work team can determine if the process is out of control or just experiencing natural variation. The natural variation may not be acceptable either, indicating that a better process is to reduce the variation to within acceptable limits (23:524).

4. Pareto Chart: This chart is based on the tendency for the majority of problems to be due to a minority of the faults. Typically, 80% of the symptoms are due to 20% of the problems. By concentrating on the primary problems, most of the variation or difficulties experienced with a system or process can be eliminated (23:550-551).

5. Histogram: This type of bar chart shows the statistical frequency distribution of a variable of interest. From this chart it can be determined how often some variable is "too low" or "too high." The work team can then determine if and when action is required to correct and improve the unacceptably low or high points (23:551).

6. Scatter diagram: These charts show the correlation between two variables. Scatter diagrams can help the work team to infer causality of problems. For example: "if defects primarily occur on days when the temperature is over 50 degrees Centigrade, the temperature-sensitive aspects of the process should be looked into (including the workers)" (23:551).

7. Fishbone chart: These charts are also know as "cause-effect" diagrams and lay out the process as a convergence of activities that result in the final product or event. Major activity lines are plotted along the result line, and minor activities that make up the major activities are plotted as short lines along the major lines. The diagram looks like a fishbone, according to Meredith. As with the process flow chart, the source of problems can often be identified based on the identified events and inputs (23:551).

Meredith further notes that in addition to the tools listed above, typically members of work teams are also trained in presentation and group problem-solving techniques. Also, workers are trained in statistical quality control concepts, and in data collection and analysis techniques. Without such training, invalid data may be collected, or inferences may be made based on bad information, which can "be more damaging than helpful" (23:551).

Summary of Literature Review and Background

This chapter provided a review of private sector literature concerning the concepts of lead time, and the order cycle time required for inventory replenishment. The various components of lead time and order cycle time were reviewed. Lead time was defined the time between the decision to order or replenish an item and its actual addition to stock. Order cycle time was defined as the time elapsed from order placement until an item is placed into the customer's inventory. For practical purposes, lead time and order cycle time are synonymous terms, except lead time includes manufacturing and assembly time while order cycle time does not include this time. Reducing lead time (or order cycle time) values and their associated variability can result in significantly better and more consistent support of customer requirements. Smaller inventory levels and safety stock requirements are required to prevent stockouts and work stoppages in an environment where lead time and order cycle time is less variable and more consistent.

Another major topic included in this chapter was a description of various analytical and simulation models devised to address uncertainty in lead time, and its effects on inventory stockage policy. First, it was found that analytical models are extremely cumbersome to work with when lead time unreliability is included in their computations. Determining the "optimal" level of stock that provides the maximum level of support at minimum cost may not even be feasible with an analytical modeling approach. In contrast, inventory simulation models have found widespread use and application in examining the effects of lead time variability on stockage performance.

For the analytical model reviewed, increased lead time usually resulted in a higher average inventory level requirement to maximize customer service and minimize costs. For the simulation models investigated, the mean and variance of lead time were found to be two of the most sensitive parameters in simulation experiments. Reduced lead time usually resulted in lower levels of inventory and less safety stock being required to achieve customer service goals. Variability of lead time was often a more dominant factor in minimizing inventory costs than variability in demand. Finally, lead time data was found to "fit" several different probability distributions, with the gamma distribution often providing the best overall characterization of lead time data. However, studies cited in this chapter focused on "procurement lead time," or time elapsed between order and receipt of material from geographically separated customers and suppliers. Direct application of the results of these studies to on-base in-transit delivery time may not be fully warranted. Additionally, variation in lead time may not fit familiar probability distributions, or may shift around in no discernable pattern.

The next major section of this chapter presented the GAO viewpoint on inventory management practices being used by private sector firms in the 1980's. While acknowledging fundamental differences in the reasons why the military services and private firms hold inventories, the "lessons learned" from civilian industry were outlined for possible application within the DoD. In the 1980's, civilian firms are pushing to reduce inventory levels while concurrently maintaining customer service levels. Many just-in-time inspired techniques are being used to achieve these reductions. They include simplifying inventory handling and decision-making, automating processes where possible, and integrating processes and flows between customers and suppliers. Additionally, the principle of continuous process improvement was found to be widespread among the companies investigated. Performance measurement to assess the flow of inventory was noted as a key technique in continually improving operations.

Current Air Force initiatives in the areas of continuous process improvement and quality management were then presented. The AFLC PACER IMPACT and QP4 programs have been devised to institutionalize continuous improvement and quality performance throughout AFLC. Use of small groups, or PATs, and statistical quality control analytical tools can be used to continuously improve not only industrial processes, but administrative and staff functions as well. The USAF R&M Variance Reduction Program has been developed to encourage continual variance reduction and process improvement. This entails defining customer requirements, or target values, and reducing variability in attempting to achieve these target values. The reduction of in-transit delivery time and its associated variability may indeed result in fewer work stoppages in Depot Maintenance due to lack of material. A brief description of SPC, Taguchi methods, and QFD was then provided.

Finally, this chapter reviewed various quality control analytical tools that could be used by a PAT to analyze problems, and to identify areas where improvement is possible. In pursuing continuous process improvement, with perfection being the ultimate goal, these tools can be invaluable in providing direction to the efforts of a PAT.

Next, Chapter III presents the methodology followed by this research effort. The overall approach used to address the research problem is outlined. The collection and analysis of actual in-transit delivery time data is discussed as well. Chapter III also describes the application of SPC as a variance reduction tool to identify opportunities for reducing the mean and variance of actual lead time data. Finally, the computer simulation of MIC inventory operations is described, as well as the experimental design devised to estimate resulting inventory performance measures based on actual and proposed reductions in in-transit delivery time.

III. Methodology

Overall Approach

A combination of methods were used to investigate and answer the research questions. Literature reviews, personal interviews, empirical data collection and analysis, and simulation using empirical data for input parameters have all been used. With regards to the overall experimental design, five main areas were investigated: 1) determination of in-transit delivery time standards; 2) analysis of actual in-transit delivery time data to determine statistical characteristics; 3) simulation of actual in-transit delivery time to determine the effects of lead time on MIC stockage performance; 4) application of Statistical Process Control techniques and tools to actual in-transit data; and 5) simulation of the effects of proposed reductions in both mean and variance of actual in-transit delivery time data on MIC stockage performance.

Procedure

To address the research problem and answer each of the research questions listed in Chapter I, the following methods were used:

1. A review of official Air Force guidance and policy publications provided initial, but only partial answers to the first three research questions concerning existing in-transit delivery time standards of performance and review practices. This initial review was provided in Chapter I.

2. Interviews were conducted with key staff members at Headquarters AFLC Directorates of Supply (HQ AFLC/DSS), and Maintenance

(HQ AFLC/MAP). Also, key staff and management personnel were interviewed at OO-ALC. The primary objectives of these interviews were to validate interpretations of official policy and guidance concerning in-transit delivery time gleaned from literature research, and to validate the appropriateness of data sources and analysis. Contacts at OO-ALC included: 1) the Maintenance Systems Laboratory (OO-ALC/MAO), the primary agency collecting in-transit delivery time research data; and 2) the Maintenance Material Control Division (OO-ALC/MAW), which is responsible for evaluating and providing guidance for overall MIC operations. Additionally, various staff and management personnel within the Distribution Directorate (OO-ALC/DS) were contacted. The Directorate of Distribution at OO-ALC is responsible for depot supply and transportation operations in supporting material requirements of all depot customers, including MICs.

Interviews were conducted on a personal, face-to-face basis where possible, or by telephone where physically visiting the respondents was not possible due to time or cost constraints. Fewer than 10 individuals were interviewed, and each individual had specific background and functional expertise. Most interviews consisted of three to five open ended questions concerning each respondent's area of functional responsibility or expertise relative to in-transit delivery time for replenishment orders to the MICs. No problems were experienced concerning the motivation of respondents to cooperate since the issue of in-transit delivery time to the MIC has received Commander and senior AFLC staff level interest in recent months.

3. Collection and analysis of actual in-transit delivery time data provided greater insight into answering the last three research questions posed in Chapter I. Actual in-transit delivery time data were collected from

Ogden ALC at Hill AFB, Utah, over a period of six months (from December 1988 to May 1989). The data were collected from two sources: 1) the G402A Exchangeable Production System, a Depot Maintenance database; and 2) actual Depot Supply local issue documents and/or DD Forms 1348-1A that document actual order and receipt times, external from any computerized database (see Appendixes A and B for samples of these documents). The data were loaded into a microcomputer spreadsheet program, and then organized and sorted by the requesting organization (MIC), transaction document number, national stock number (NSN), date and time of in-transit start or stop transaction, and so on. Descriptive statistics, by MIC, on means and variances of in-transit delivery times were computed. These statistics were used to describe the in-transit time for items requested by the MICs, and compared to HQ AFLC standards. Kolmogorov-Smirnov "Goodness of Fit" tests were conducted on the data using a distribution-fitting computer program to determine possible theoretical probability distributions that adequately characterize the observed lead time data.

4. A review of civilian and private industry literature was performed to determine if there were Variance Reduction, Total Quality Control, and Statistical Process Control techniques or methods applicable for reducing the mean and variance measures of lead times. Also, recent Air Force and AFLC initiatives to promote Quality Control and Variance Reduction techniques were investigated for possible applications. This phase of the research procedure provided greater insight for determining what actions have, can, and will be taken to: 1) measure in-transit delivery time, and 2) provide methods to improve the overall delivery process. The third, fourth and fifth

research questions discussed in Chapter I are addressed by this segment of the research procedure.

Additionally, recent and planned initiatives in various process automation, enhanced data systems, and improved operating procedures and policies concerning MIC operations were investigated through interviews. Since documentation on more recent initiatives is scarce or currently in work, interviews were the primary data collection tool used to gather data in this area. Additionally, recent organizational and procedural initiatives impacting in-transit delivery times, such as the PACER INTEGRATE and the Distribution Support Center (DSC) conversion, are briefly described in Chapter IV. Findings on recent or planned data systems and automation initiatives such as the Stock Control and Distribution System (SC&D) are briefly outlined in Chapter IV as well.

In a similar fashion to the previous interviewing scheme noted, these interviews were conducted with three individuals having specific, functionally-oriented knowledge concerning current Air Force and AFLC initiatives in the areas of automation, integration and continuous process improvement of in-transit delivery of replenishment assets to the MICs.

5. Statistical Process Control techniques and tools were applied to analyze the in-transit data to see if excessive lead time and its associated variability might be reduced. This portion of the overall research procedure resulted in answers to the research questions concerning the application of quality control, variance reduction, and continuous improvement principles to improving the process of asset delivery to MICs.

6. A SLAM II computer simulation model was used to assess the effect that in-transit delivery time parameters may have in terms of

expected backorders (unfilled requests for replenishment), Line Item Fill Rates (LIFR), and other inventory performance measures. The simulation segment of the research procedure provided insight into answering the final research question concerning the use of simulation to demonstrate the impacts of varying in-transit delivery times upon material availability in the MICs. Theoretical probability distributions, determined from actual observed lead time values, were used to evaluate the impact of reducing the mean and variance of in-transit lead times. These impacts were estimated using the computer simulation model.

Analysis of In-Transit Delivery Time

The method for analyzing actual in-transit lead time data was to collect a census of lead times over a six month period for six MICs at Ogden Air Logistics Center (OO-ALC). These data were collected from the G402A Exchangeable Production System database as noted earlier in this chapter. From each population of MIC data, a random sample of 251 transaction document numbers was selected per month for the six month period. The in-transit delivery time for a given MIC replenishment order was computed by subtracting the transaction start time and date from the transaction stop time and date. This value provided an estimate of the elapsed time from DS initiating a stock replenishment shipment to MA acknowledging receipt of the material.

A sample size of 209 was required to estimate the population mean in-transit time to within plus or minus 0.5 days at the 95% confidence level. The formula for computing the sample size of 209 was:

$$n = \frac{\left(Z_{(\alpha/2)}\right)^2 (\sigma)^2}{E^2} \qquad (2)$$

where

n = Required Sample Size

$Z_{(\alpha/2)}$ = Z-value with an area to the left and right tails of a standard normal distribution curve ($Z = 1.96$)

σ = Population standard deviation (can be estimated as 3.68 days from information based on McBride's study (22:55))

E = Tolerable Error Limit (0.5 days) (26:130-131)

This sample size was increased to 251 per MIC to ensure that at least 209 transactions were available for analysis after unmatched and unusable transactions were purged from the database. For those MICs having less than 251 transactions during a given month, all usable and matched start and stop transactions were examined.

Additionally, a random sample of local issue documents and DD Forms 1348-1A was drawn by OO-ALC/DS personnel. The documents allowed determining significant differences existed between in-transit lead time data extracted from the MA G402A data system and data derived from actual issue/receipt documents.

The in-transit time as measured by the G402A system includes "the time it takes from when the MIC personnel certify receiving the material to when the in-transit is cleared back to the D033" (22:55). McBride used a PERT-beta distribution to estimate a mean time to clear the transactions of

5.146 hours (0.225 days) based on pessimistic, optimistic and the most likely times required to clear the transaction (14:56). This time lag may also be estimated from the issue documents, which are supposed to be signed by MA personnel and annotated with the time and date of physically receiving the material.

From an initial collection of in-transit data from the G402A system for the months of December 1988 and January 1989 covering 10 MICs at OO-ALC, a sample size of 209 local issue documents was required to estimate the population mean in-transit delivery time to within plus or minus 0.5 days at the 95% confidence level. This sample size was derived using Equation 2. Again, the sample size was increased to 251 to ensure that at least 209 transactions were available for analysis after unmatched and unusable transactions were purged. The 10 MICs included in this sample are listed below with their respective areas of maintenance responsibility:

1) MCC (aircraft repair);
2) MDD ("black boxes" for aircraft and missiles);
3) MFF (landing gear);
4) MBB (sheet metal repair and fabrication);
5) MLL (missile transportation vehicles and other "rolling stock" repair);
6) MHH (repair of assets used by the missile test range at OO-ALC);
7) MEE (aircraft engine repair);
8) MAX (missile guidance systems);
9) MGG (test equipment);
10) MSS (missile and ordinance guidance systems).

The resulting mean difference between the start and stop times and dates as computed from this sample of issue documents provided another estimate of the in-transit time between DS and MA MICs. This estimate was compared with the mean start and stop time for the same transaction on the

G402A database to determine if there was a significant time lag between when MA actually received the property and when the in-transit transaction was cleared via the G402A back to the D033. This allowed estimating the average lag time required to clear transactions through the formal G402A and D033 computerized information systems. Applying the paired difference t-test or the Wilcoxon nonparametric signed rank test for paired differences allowed determining if there was a statistically significant difference between the clearance time and date annotated on issue documents, and the time and date for the same transaction on the G402A database.

Variables for Analysis. To investigate actual in-transit delivery time, data on individual replenishment issues to the MICs were required. Within the MA parts request history database maintained on the G402A system, the dates and times of in-transit start and stop transactions are stored. From this data, the duration of the in-transit delivery time for each item delivered to the MICs was derived. As noted earlier, the time between the in-transit start and stop transactions represents the time it takes for MIC in-transit replenishment issues to be gathered from DS, transported to the MA area, accepted through the DS/MA receipt certification process, and finally added to the MIC inventory balance on the G402A system. Therefore, the primary data of interest are the processing dates and times for each in-transit start and stop transaction. Other data elements of interest include the NSN of the item requested, the quantity requested, the MIC identifier code, and other descriptive elements for stratification of extracted data.

It should be noted at this point that in-transit times maintained and computed from the G402A database are based on continuous clock hours and calendar days. Recall that the AFM 67-1 delivery standard for MIC replenishments was no later than 12 working hours, or 1.5 working days. It was not feasible to exclude holidays, weekends, or different MIC shift schedules from the data collected. The reader should bear this in mind in all succeeding discussion and analysis of in-transit delivery times.

Once mean and variance measures of the actual in-transit delivery time were derived and stratified, actual lead time measures served as input parameters to the computer simulation model. The simulation model was used to compute performance measures that may result from actual in-transit delivery time mean, variance and theoretical probability distribution parameters. The simulation outputs include MIC stockage performance indicators which are described in a later section of this chapter. The data was then evaluated for possible variance reduction opportunities using statistical process control tools and techniques. Next, proposed reductions in the mean and variance of lead time were input into the simulation model to analyze the effects that mean and variance reductions have on simulated inventory stockage performance. The resulting performance measures for both actual lead time and proposed reductions in lead time were then compared.

Data Collection and Transformation. The in-transit data collected represented six months worth of transactions. As noted in Chapter I, both indirect and direct material replenishments were included in the research population. Additionally, both consumable and reparable item transactions (for ERRC XB3, XF3, and XD2 items) were collected and analyzed. The Systems Laboratory within the Ogden Air Logistics Center Directorate of Maintenance (OO-ALC/MAO) used an ENFORM database interrogation program to collect in-transit data from the G402A system, and transferred the data to MS-DOS compatible floppy disks. The data retrieved included the NSN, MIC identifier, and the times and dates for the in-transit start and stop. A sample of the data collected and the ENFORM program source code are shown in Appendixes C and D respectively. For instance, in Appendix C the first transaction listed was for NSN 533001248545 1AQ. This is the "start" transaction. Immediately following the "start" transaction is the corresponding "stop" transaction for the same NSN. This is denoted by the "CL" listed under the "AC-SF" column heading in the second line. The corresponding times for the start and stop transactions are seen in the last two columns.

The data provided by OO-ALC/MAO was then uploaded to a VAX mainframe computer. Each data file represented a census of all stock replenishment transactions for a given MIC for one month. In hard copy, each file varied in total page length, and there was a maximum of 60 transactions printed per page on the output listing. In the first step of the sampling process, a random listing of page numbers was used to select the page from which a sample transaction would be pulled. A random listing of transaction numbers then determined the location on a given page from which a sample transaction was selected. or example, a random page number of 25 and a transaction number of 35 would result in a sample being pulled from page 25 of a given MIC replenishment transaction listing. The 35th transaction on the page would be selected for the sample.

A microcomputer spreadsheet program was used to generate random numbers required to pull a random independent sample of 251 transactions per MIC for each month. The following formula was used to generate 251 randomly-selected computer listing page numbers from which sample transactions were drawn using the microcomputer spreadsheet program:

$$A = \lceil ((ab) / 60) + 1 \rceil \qquad (3)$$

where

A = Random page number

a = Spreadsheet-generated random number between 0 and 0.99999

b = Total number of transactions on a computer listing

Additionally, in order to select the particular transaction to be sampled from a given random computer listing page (or "A" as defined in the equation above), the following transformation was made: The modulus of dividing A by 60 plus 1 identified the selected sample transaction number. After a sample transaction file was developed for each MIC and month in the sample period, the in-transit time for each sample replenishment was computed by subtracting the transaction start time and date from the appropriate transaction stop time and date. Mean and standard deviation values for each MIC and for each month were then computed, and are presented in Chapter IV.

The six MICs included in the data collection population were chosen to parallel the MICs studied by McBride, and to "represent a broad cross section of types of end-item workloads" (22:36). In consideration for end-item workload, the following four MICs were examined: 1) MCC (aircraft repair); 2) MDD ("black boxes" for aircraft and missiles); 3) MFF (landing gear); and 4) MBB (sheet metal repair and fabrication). Also, two additional MICs were examined. These two MICs were included to test the hypothesis that an influencing factor in overall in-transit lead time may be the relative distance of a given MIC from the DS warehouse, where all delivery actions start.

Therefore, this analysis included both MICs located relatively near and distant from DS warehouses. One MIC was chosen based on its relative close proximity to DS warehouses, while another MIC was chosen for its relative distance from DS warehouses. MIC MLL, which supports repair of missile transportation vehicles and other "rolling stock" was chosen to represent MICs very close to a DS warehouse. MIC MHH, which supports repair of assets used by the test range at OO-ALC, was chosen to represent MICs relatively far from a DS warehouse. After the in-transit lead time parameters were established for each of these MICs, a simulation analysis of lead time impact on stockage performance was accomplished.

Simulation of In-Transit Delivery Times

Overview of McBride's SLAM II Simulation Model. McBride developed a SLAM II computer simulation model to evaluate different MIC stockage policies in terms of their expected performance (22). The model generates actual MA production line demands for a single item of stock based on an exponential distribution, implying Poisson distributed demands with varying days between requests and number of units requested. If the MIC on-hand inventory stock level is less than the reorder point, a request for stock replenishment is generated to DS, with the item scheduled to arrive at an "order and ship time (O&ST)" later (22:45). His O&ST is the MIC in-transit delivery time. McBride's SLAM II program is a combination of SLAM II network statements and FORTRAN insert subroutine programs. The FORTRAN subroutines were written to collect performance statistics and to format specific reports for the simulated 15 years (30 six-month cycles) of operation. The program consists of three files: MIC. DAT, which contains the SLAM II network statements; MAIN. FOR, which holds the FORTRAN subroutines that model the inventory policy and generate custom reports; and PARAM.INC, which initializes and dimensions the FORTRAN arrays used in the MAIN.FOR program(22:43-44).

The MIC.DAT program controls the timing and sequencing of events within the inventory system, modeled as a network. The network generates orders based on an exponential distribution with a specified β mean days between requests. A Poisson distribution is used to generate the number of units requested for the item under consideration, where the average order size is λ (and λ is greater than or equal to 1). At the end of each day in the simulation, copies of the order requests are accumulated. The total number of demands are recorded to a statistical register for later determination of Daily Demand Rate (DDR) statistics, MIC stockage objectives, and reorder points (22:44).

The original copy of the demand is processed by a request subroutine that checks if a total fill of the request can be made from DS on-hand stock. A partial fill with partial backorder, or a total backorder may also result if the on-hand stock is not sufficient to meet the total quantity requested. If the request can be filled, either totally or partially, the on-hand stock is reduced accordingly, and statistical observations are made on the resulting fill rates. Backorders that may occur are held in a file awaiting possible fulfillment from subsequent stock replenishments. Time persistent statistics are collected on backorders to determine the average number of backorders, and backorder-days (22:44-45).

After any request for stock, a releveling routine is called from a FORTRAN subroutine to see if the inventory position (on hand + on order - backorders) is less than the most recently computed MIC reorder point. If the inventory position is below the reorder point, a stock replenishment request sent to DS, and a shipment is scheduled to arrive at the MIC at a later time. As mentioned earlier, this time is is known as order and ship time (O&ST), or the in-transit delivery time. In McBride's study, the actual O&ST was randomly selected based on a lognormal distribution using observed mean and variance values from an actual MIC at OO-ALC (22:44). McBride determined these O&ST parameters based on a 30-day sample of in-transit data from the single MIC as briefly outlined in Chapter I. As noted earlier, the O&ST, or in-transit delivery time is the primary parameter of interest in this study.

Every seven days in the simulation, the model calls for a recomputation of the stockage levels. The model is run for 200 days to accumulate an initial 180 days of historical simulated data, and to allow the system to get past the initial transient period. This enables the simulation model to achieve "steady state" status. At day 200, the statistical registers that collect performance statistics are cleared, and performance measures are collected from this point in simulated time forward (22:44). This practice is perhaps best explained by A. Alan B. Pritsker in his book Introduction to Simulation and SLAM as noted below:

> When the purpose of our analysis is to study the steady-state behavior of a system, we can frequently improve our estimates of the mean by beginning the simulation in a state other than empty and idle. Steady-state behavior does not denote a lack of variability in the simulation response, but

specifies that the probability mechanism describing this variability is unchanging and is no longer affected by the starting condition. (28:43)

The start up transient period for the stock level computations is set at approximately 180 days because both the DS and MA inventory stockage models require at least 180 days of demand history before computing demand parameters. An extra 20 days was used beyond the 180 to allow for the receipt of any outstanding MIC replenishments that were ordered during the preceding initial 180 day period in the simulation (22:46).

Every 180 days after the transient period, the network calls the FORTRAN output subroutine which calculates summary statistics. Included in semi-annual reports are measures of the observed unit fill rates (UFR), the line item fill rates (LIFR), the average number of units requested, number of backorders and backorder-days, and average on-hand inventory, in addition to other performance measures. Each of these measures is defined in greater detail below. At the end of the simulation time period (200 days for the transient period plus 30 subsequent six-month sequential periods), an overall summary report is created that includes grand means and standard deviations of the performance measures. This multiple-batch sequential method of simulating was used to reduce possible bias and random variances. It also provides enough observations to apply the Central Limit Theorem, which states that given enough observations, generally 30 or more, of random variable $\bar{x}$, the mean of $\bar{x}$ ($\bar{\bar{x}}$) is distributed approximately normally. The standard deviation of $\bar{\bar{x}}$ is equal to the standard deviation of observations of $\bar{x}$ divided by the square root of the number of computed $\bar{x}$. The standard deviation of $\bar{\bar{x}}$ is also known as the standard error (22:45-46). Through the application of the Central Limit Theorem, confidence intervals and statements of reliability for the estimated means and variances of simulated performance measures can be computed.

In order to evaluate the simulated performance of the alternative models, McBride made multiple runs of the simulation program for a wide range of items to come up with resulting performance measures. As alluded to earlier, those measures were: 1) fill rates at the unit and line item level; 2) the number and duration of expected annual backorders in number and duration; and 3) average level of MIC on-hand inventory (22:35). McBride noted that the D033 TVA report ("Depot Maintenance Material Support") outlines the performance objectives for MIC and D033 support to MA material requests. The primary MA MIC support performance measure is the Line Item Fill Rate (LIFR), for which a 95% objective exists (22:19; 4:43-8). A sample of an D033 TVA report is provided in Appendix E. McBride distinguishes the LIFR from the Unit Fill Rate (UFR) as noted below:

> The line item fill rate represents the percent of requests that were totally filled. A unit fill rate would represent the total percentage of units requested that were filled. For example, if a request for ten units is issued six units and the other four units are backordered, the line item fill rate is zero and the unit fill rate is 60 percent. (22:20)

McBride varied the following input parameters for each run of the simulation: 1) average number of days between requests, or β ; 2) average quantity per request, or λ ; and 3) type of theoretical demand distribution. By using various combinations of demand distributions, he sought to infer what range of distribution parameters would be required for a given model to meet the 95% LIFR objective for the MICs (22:40-41).

One key assumption of McBride's model, and one that holds for this analysis as well, should be noted at this point. The simulation program logic assumed that if an item had a computed MIC stock level, then the D033 Depot Supply system always had enough stock on hand to fill MIC stock replenishment requests. In other words, the in-transit delivery time reflected only on-base warehouse retrieval and transportation time from DS to MA for stock replenishment. The model did not attempt to account for procurement lead time, procurement order and ship time, or backorders to the D033 system. Since this is an optimistic assumption, McBride notes that the simulated fill rates are also optimistic, and should be considered "an upper limit; the performance of the MICs must be considered in light of replenishment support from DS (D033)" (22:57-58).

<u>Experimental Design of Simulation Analysis</u> The general objectives of the simulation analysis in this study were to examine the effects that different mean in-transit delivery times, measures of dispersion (variance), and statistical probability distributions have on observed the LIFR and other performance measures. The primary input parameters are β, λ , the in-transit delivery time (or O&ST), and the tvpe of probability distribution for the O&ST (such as normal, lognormal, gamma, exponential or beta). In the simulation experiments, only MICs MCC, MDD and MFF were analyzed since McBride did not collect demand data for MICs MBB, MHH, and MLL.

The demand data collected and analyzed by McBride provided the basis for the demand parameters used in this research (Table 2). For the number of days between demands for a given item (β), three values (low, medium and high) were used (22:52, 53, 86). The average number of units per request (λ) also varied by MIC (22:51). For the purposes of this

Table 2. Simulation Experimental Design Overview

	MIC		
	MCC	MDD	MFF
DBR (β) Relative Value			
LOW	3	3	9
MEDIUM	12	28	22
HIGH	110	110	110
UPR (λ)	2	6	9
β , λ Distribution	CP	PP	PP

simulation analysis, these values were rounded up to the next whole integer. The final demand parameters of interest in the simulation experiments were the distributions of β and λ. McBride found that the majority of MIC MCC items could be classified as having a constant λ value and a Poisson-distributed β value (denoted CP) (22:52). For MICs MDD and MFF, however, McBride determined that their λ and β parameters were both Poisson-distributed (denoted PP) (22:51, 53).

These demand parameters were selected to maintain a high degree of comparability with McBride's results. The goal of this study was not to duplicate his efforts with respect to MIC demand analysis, but to extend his results to areas dealing with in-transit delivery time impacts. Table 2 illustrates the basic experimental design used in this study to examine the effects that various parameters such as λ and β (as well as their respective theoretical probability distributions) have on MIC stockage performance.

Several changes were made to McBride's model logic to incorporate stockage guidelines and recent changes in MIC stockage policy, First, the maximum amount of in-transit delivery time, or O&ST, that could occur in the simulation was set at 20 days. This was added to McBride's model because AFM 67-1 indicates that if the in-transit transaction is not cleared in 21 days, the item is considered a "delinquent in-transit" (11:6-3). If a delinquency occurs, the MIC inventory balance will be increased by the order amount automatically by the D033 system, and the MIC level will be "frozen" for manual inventory (11:6-3). In other words, if the in-transit takes longer than 20 days to be received by the MIC, the item is frozen, meaning that no more transactions can occur until the delinquent in-transit is resolved. The net result is that no in-transit should take more than 20 days before manual intervention by DS and MA personnel. Another change to McBride's model was incorporated into the program logic based on the earlier discussion in Chapter I of the "15/7" maximum stock level and reorder point inventory policy. That is, 15 days worth of stock was used as the maximum stock level, or "order-up-to" level, and 7 days worth of stock was used used as the reorder point for replenishment orders. Finally, it is important to remember that the LIFR and other performance measures output from the simulation models represent the estimated results for a single theoretical item of stock characterized by the O&ST and demand parameters and probability distributions described earlier in this chapter.

Statistical Process Control (SPC) Applications and Analysis Overview

The approach to this segment of the overall analysis process includes applying SPC, briefly described in Chapter II, as a variance reduction tool to analyze the in-transit delivery time data collected. The overall objectives of analysis using these techniques were: 1) to show the feasibility of using SPC techniques to analyze lead time data to reduce its overall mean and variance; and, 2) to display possible delivery time trends that would merit the attention of a PAT to resolve. Control charts are the basic tools used in SPC, and can be used to analyze in-transit delivery time with respect to upper and lower control limits. Control charts allow the analyst to separate chance variation in a system or process, and variation due to a system being "out of control" (23:550). Assignable causes of variation can be detected, and control actions or adjustments can also be suggested by control chart analysis. The six MICs included in this study were examined to highlight the MIC which exhibited the highest observed mean and standard deviation of lead time. After determining which MIC and which month in the study exhibited the highest and most variable lead times, statistical process control charts were developed to further analyze the process. Areas where the delivery process for the selected MIC could be considered "out of control" can be indicated by using these control charts. With further study and scrutiny, the assignable causes of these points of variation could be identified and attacked by a PAT. The SPC control charts are displayed and discussed further in Chapter IV.

Summary

Chapter III presented the methodology used to investigate and answer the research questions. The approach and procedures outlined in this chapter have been used to: 1) determine in-transit delivery time standards; 2) analyze statistical characteristics of actual in-transit delivery time; 3) simulate empirical in-transit delivery time values to estimate their effects on MIC stockage performance measures; 4) apply SPC tools to identify process improvement opportunities; and 5) simulate the effects of proposed reductions in the mean and variance of lead times on MIC stockage performance measures.

Chapter IV presents and analyzes the results of the various methods conducted as described in Chapter III. The resulting findings from all research, interviews, data collection and analysis, and simulation experiments are included in Chapter IV.

IV. Findings and Analysis

Overview

In this chapter, results of interviews to discover what the existing in-transit delivery time standards are, and how they were established and monitored are presented. A review of AFLC initiatives planned and in progress to address the problem of excessive in-transit delivery times is also provided. Then, analysis of in-transit delivery time data is discussed. First, empirical lead time measures observed for MICs included in the sample described in Chapter III are presented. Next, attempts to fit these data points to theoretical probability distributions are outlined. Analysis to determine if there was a significant difference between G402A-maintained in-transit data and off-line issue document in-transit data is then described. The next major area of data analysis involves deriving through simulation the estimated inventory performance of three MICs using the empirical in-transit delivery time data as primary input parameters. The application of SPC is then examined to identify opportunities for the reduction of lead time mean and variance. Finally, the impact that proposed reductions in lead time mean and variance values have on inventory stockage performance is evaluated.

Review of In-Transit Delivery Time Standards

In order to answer the first three research questions presented in Chapter I, an interview was conducted with Mr. Leslie K. Clarke, III. Mr. Clarke is the Chief of the Supply Resources Management Division within the Headquarters AFLC Directorate of Supply (HQ AFLC/DSSM). First, Mr. Clarke was asked if the current standards outlined in the USAF Supply Manual, AFM 67-1, Volume III, Part Two for in-transit delivery times of material to the MICs were the correct and accurate (11:21-10). The interpretation of a "12-hour," or "1.5 working day" delivery time standard for MIC stock replenishment orders, which are assigned Delivery Priority Code 6, was confirmed by Mr. Clarke (3). Additionally, Mr. Clarke reported that the current standards have evolved as heuristic goals that were thought to be adequate time frames for on-base delivery and receipt of material. There have been no formal studies of what the actual capability for material delivery may be at the different ALCs. The "12-hour/1.5 working day" delivery standard for Delivery Priority 6 MIC stock replenishment issues was more an informal estimate of the on-base transportation system's capability (3).

The third research question concerning whether any actions are being taken to determine if the existing standards are being met, and whether they are adequate, realistic, and accurately measured, is being addressed by Mr. Clarke's office. The Headquarters AFLC Directorate of Distribution has initiated a study to collect, analyze and report on DS delivery timeliness at each of the ALCs (14). The study plan developed by Mr. Clarke as part of this tasking noted that there is no current command-wide method to collect and analyze in-transit delivery time. One of the end results of the year-long study, to be completed in August or September 1989, will be analysis and documentation on what in-transit delivery times actually are at the ALCs. Also, recommendations on what the delivery standards should be are another expected outcome of Mr. Clarke's study (3).

There are some characteristics of the HQ AFLC study of in-transit delivery times experienced at the ALCs that should be noted at this point. First, the HQ AFLC study includes all Delivery Priority transactions, from 1 to 6. This is more comprehensive than the population studied in the current effort, which includes only direct and indirect stock replenishment issues to MICs (Delivery Priority 6). Additionally, the HQ AFLC study was based solely on sampling local issue documents. The elapsed delivery time was determined as the difference between the time when the document was produced until it is signed by a representative of the requesting organization (14). This method is in contrast to the procedure used in the current study, where a combined data collection scheme based on G402A data and local issue documents was used as described in Chapter III. It is interesting to note that according to Mr. Clarke, the local issue documents included in their sample were not always signed and annotated with the time and date of receipt by the receiving organization. Those transactions where a time or date was not annotated on the document were considered as "on-time" deliveries (3). Additionally, the AFLC study effort is based on transactions that occurred in calendar year 1988, while this effort includes only six months of transaction data from 1 December 1988 until 31 May 1989 (3). The sample size of transactions to be analyzed was based on FY 88 average monthly issues. For OO-ALC, the assigned sample size per month was 364 transactions (14).

This section provided answers to the first three research questions discussed in Chapter I. The next section describes provides initial investigation into the fourth research question. As a starting point, a review of AFLC initiatives planned and in-progress is necessary.

Review of AFLC Initiatives Addressing Excessive In-Transit Delivery Time

Many of the areas noted by the GAO in their report on private inventory management practices that may be applicable for use in the DoD are indeed being explored and pursued within AFLC. Many initiatives are either planned or in place to simplify inventory handling and decision-making, to automate processes where possible and cost-effective, and to integrate processes and flows between customers and suppliers. The just-in-time philosophy has also found support within AFLC as reflected in the recent draw-down of material held in the MICs from "30 days worth of stock" to "15 days worth of stock," as noted in Chapter I. Additionally, a recent initiative named PACER INTEGRATE has been developed to consolidate "the complex, fragmented supply and transportation processes and inventories of depot maintenance support in the Directorate of Distribution to the greatest possible extent" (6:1).

According to Major Joseph Reuwer, Chief of the Depot Maintenance Distribution Support Division in the Headquarters AFLC Directorate of Distribution, the PACER INTEGRATE project involves the establishment of "Distribution Support Centers (DSCs)" to essentially perform the supply-related tasks currently accomplished by MIC personnel (29). The DSCs are envisioned to "provide a full range of supply and transportation services directly into the maintenance work centers" (6:1). The PACER INTEGRATE program is planned to start on a test basis at Ogden ALC in January 1990 (29).

In addition to initiatives to simplify and integrate processes, and to reduce inventory levels, several actions have been taken to automate processes where possible and cost-effective. At Ogden ALC alone, there are several Automated Storage and Retrieval Systems and Mechanized Material Handling Systems. The Automated Warehousing System (AWS) and small parts storage warehouse (or Automated Storage Module) in the OO-ALC Distribution Directorate are state-of-the-art examples in automated, high density storage and distribution systems. OO-ALC has had the AWS in place since July 1987, and the program has since spread in application to the other ALCs in AFLC (2:17). Extensive use of conveyors and wire-guided vehicles (both manned and unmanned) can be seen throughout the DS storage and distribution complex. There is also a pneumatic tube delivery system that transports smaller assets no larger than 10 x 24 inches and less than 25 pounds directly to eight MA work areas. Systems such as these place the OO-ALC Directorate of Distribution in the forefront as a leader in the effective use of automated processes, and in realizing delivery lead time reductions.

Another area where AFLC is simplifying, integrating and automating inventory processes and flows is in the area of information required to track assets from the time an order is placed until it is received by the customer. The AFLC Logistics Management System (LMS) modernization program was initiated to address "data processing problems in four AFLC core functions--requirements development, acquisition, storage and distribution, and maintenance" (24:81). Under LMS, there will ultimately be seven new information systems linked together by two major communications systems that will form an interactive network, placing "a wealth of diverse information in the hands of decision-makers" (24:81).

One of the seven systems planned for development within the LMS is the Stock Control and Distribution System (SC&D). SC&D will result in reduced depot processing time and increase the ability to track and deliver assets to end users. The system is currently planned for implementation and Initial Operational Capability (IOC) at Ogden ALC in December 1989. The other ALCs in AFLC are programmed to reach IOC also during FY 90 (33). The primary benefits expected from SC&D include a reduction in AFLC's pipeline inventory and a vast improvement and reduction in asset in-transit delivery times, yielding increased aircraft availability rates and fewer lost hours of production due to the lack of parts (24:83).

The Document Control Record (DCR) process currently included in the SC&D data system architecture is designed to provide an on-line tracking system for controlling all material movement between the Directorates of Distribution (DS) and Maintenance (MA) at all the ALCs. The purpose of DCR is to automate signature receipting of assets through the use of bar code technology in all of the material movement functional areas. Also, DCR provides a central repository of receipt, issue, turn-in and shipment auditable historical transaction images. As a result, DCR replaces manual signature receipting with bar code scanning for more accurate and automated material tracking. Additionally, microfilm storage of historical transaction documents will be converted to an on-line data storage system. While most of the required data systems and capabilities are currently in place or nearing complete development to implement the DCR process, adequate funding for full-scale implementation and use of DCR is not anticipated until FY 92 (33). Additional software development and hardware acquisitions (such as computer terminals, bar code readers and peripheral equipment) will be required before full-scale implementation is possible (33). Initiatives such as the SC&D/DCR process data automation had much promise in easing the burden and increasing the accuracy involved in collecting and analyzing appropriate lead time data. The next section presents an analysis and evaluation of lead time data pursued for this study.

Data Analysis and Evaluation

Empirical Mean and Standard Deviation Measures. Table 3 displays the empirical mean and standard deviation measures of in-transit delivery time for the six MICs sampled over the 1 December 1988 to 31 May 1989 time period. The corresponding samples sizes drawn for each MIC and each month in the sample are shown in Appendix F. As noted in Chapter III, a sample size of 209 or more was required to estimate the population mean in-transit time to within plus or minus 0.5 days at the 95% confidence level. All random samples of MIC in-transit transactions exceeded the required sample size to achieve this level of confidence. Those samples sizes marked with an asterisk in Appendix F were the result of 100% census samples. As noted in Chapter III, for those MICs that had less than 251 transactions during a given month, a 100% census of usable and matching start and stop transactions was accomplished.

The observed values for mean and standard deviation of in-transit delivery time presented in Table 3 should be evaluated in light of the "1.5 working day/12 working hour" delivery standard prescribed in AFM 67-1 and outlined in Chapter I. Note that the time values presented in Table 3 represent continuous clock hours and calendar days. Holidays, weekends and other production down times (some MICs operate 24 hours a day, while others operate only one or two shifts per day) were not distinguishable in the G402A database. That is, the time between notification of delivery and

Table 3. Empirical In-Transit Delivery Time Data in Days-G402A

MIC Identifier		December	January	February	March	April	May
		Month					
MCC	$\bar{x}$	6.593	3.550	4.779	3.851	4.541	4.234
	s	3.774	2.995	3.455	3.578	3.647	3.349
MDD	$\bar{x}$	3.457	1.835	1.650	2.054	1.819	2.391
	s	2.461	1.603	1.509	1.702	1.319	1.927
MFF	$\bar{x}$	2.995	1.824	1.671	1.347	1.525	1.926
	s	2.740	1.864	1.596	1.505	1.640	1.922
MBB	$\bar{x}$	4.622	3.414	2.692	2.394	2.204	2.334
	s	3.256	2.413	2.457	2.023	1.816	1.668
MHH	$\bar{x}$	6.152	3.531	3.543	4.017	3.880	3.759
	s	4.148	3.982	3.271	4.731	4.197	3.425
MLL	$\bar{x}$	3.002	1.600	1.942	1.810	3.154	2.316
	s	2.563	1.452	1.420	1.397	3.006	1.492

the actual receipt and clearance of the transaction is measured on a continuous clock hour versus working hour, and calendar day versus working day basis.

The first figure presented in Table 3 for a given MIC and month is the observed mean lead time in days (or "$\bar{x}$"), while the number immediately below it is the observed standard deviation in days(or "s"). For example, for MIC MCC in December, the observed mean lead time was 6.593 days, and the corresponding standard deviation of lead time was 3.774.

A general overview of the data in Table 3 reveals that the lead time statistics for December are somewhat higher than the other five months in the sample. It is believed that this is due to the many holidays and leaves that occur among both MA and DS personnel, in addition to production draw-downs during the winter holidays. In some cases (especially for MICs MCC and MHH), a dramatic decrease in mean lead times was observed between December and the subsequent months in this study. Therefore, December lead time measures seem to be influenced by factors outside of the scope of this study, and are not representative of the true on-base delivery system's capability.

In general, MIC MCC experienced higher mean and greater standard deviation lead time values by month than the other MICs. This supports the conclusion that the aircraft maintenance area experiences higher in-transit delivery times as measured by the G402A data collected and analyzed in this study. Additionally, MIC MHH was evaluated due to its relative distance from the DS warehouse complex at OO-ALC. It was hypothesized in Chapter III that MHH would experience higher delivery lead times due to its relative greater distance from the DS warehouse complex than the other MICs in this study. The data displayed in Table 3 generally support this hypothesis in that the mean and standard deviation measures for MHH are generally higher than the other MICs, with the exception of MCC. In contrast, MIC MLL was selected for study due to its close proximity to the DS warehouse complex. As shown in Table 3, the lead time mean and standard deviation measures are lower in general for MLL than the other MICs, with the exception of MFF. The close proximity of MIC MLL to the DS warehouse appears to be a strong contributing factor in the lower observed in-transit delivery times experienced by this MIC.

Probability Distribution-Fitting of Empirical Data. Data collected for MICs MCC, MDD and MFF in this study were analyzed to determine theoretical probability distributions that might adequately characterize their in-transit delivery times. This was necessary in order to determine the impact that both empirical and proposed reductions in mean and standard deviation measures of in-transit delivery times had on various measures of inventory performance. Theoretical probability distributions found to adequately describe the data were used as input parameters to the simulation model to provide an inventory performance baseline for further analysis.

The last five months of in-transit delivery time data samples (January 1989 to May 1989) were combined into a single data sample for each MIC. As noted earlier, the data collected during the month of December resulted in mean and variance measures that were higher than the remaining months of the sample. For this reason, December's mean and variance measures were believed to be unfair characterizations of delivery lead times, and were therefore excluded from further analysis.

With the remaining 5 months of data, a 10% trim mean procedure was used to refine the data sets for each MIC. The data for each MIC were sorted in ascending order of lead time values, and the smallest 10% and largest 10% of the data values were excluded. This procedure yielded " 'a measure of that is neither sensitive to outliers as the mean nor as insensitive as the median' " (22:54). The data set for MIC MCC contained 1174 observations prior to 10% trim mean application, and 940 observations after editing. The data set for MIC MDD contained 1220 data points prior to editing, and resulted in a trimmed data set size of 976. Finally, the MIC MFF data set had

1228 data points prior to editing, and 982 observation after application of the 10% trimming procedure.

Kolmogorov-Smirnov (KS) tests were then performed on each of the MIC's 5 month data sets to test the "goodness-of-fit" of 10 different theoretical probability distributions. The AID distribution-fitting computer program developed by Pritsker and Associates was used to test and fit this data. Appendix G provides an overview of the KS tests performed as well the results. In all cases, the null hypothesis was that the data sample being tested was distributed according to the specified probability distribution, versus the alternative hypothesis that the data did not come from the specified distribution. The significance level for all KS tests performed was 5%. The distribution-fitting efforts for each of the 3 MICs follow.

MIC MCC Goodness-of-Fit Tests. As shown in Figure 5, the KS test failed to reject the hypothesis that the data were from a beta distribution with μ = 3.626 days, σ =1.848 days, α = 0.772, and β = 1.276 (the minimum point for the hypothesized distribution was 1.11 days, and the maximum point was 7.767 days). Figure 5 also shows the hypothesized Cumulative Distribution Function (CDF) of the data, as well as confidence limits that show the rejection areas that would indicate the hypothesized distribution was not appropriate. As can be seen from Figure 5, the CDF falls within the confidence limits. Additionally, Figure 6 illustrates the data's actual relative frequency distribution with the vertical histogram bars, and the Probability Density Function (PDF) for the hypothesized beta distribution shown by the solid curved line. Thus, the hypothesized beta distribution portrayed in Figures 5 and 6 was used to simulate in-transit delivery times for MIC MCC.

KOLMOGOROV-SMIRNOV TEST

SAMPLE SIZE	= 940
LEVEL OF SIGNIFICANCE	= 0.05
CRITICAL VALUE	= 0.0444
K-S TEST STATISTIC	= 0.0370

THE K-S TEST STATISTIC IS
LESS THAN THE CRITICAL VALUE

THERE IS NO SAMPLE EVIDENCE
AGAINST THE NULL HYPOTHESIS

HYPOTHESIZED DISTRIBUTION: BETA

PARAMETERS:

MEAN	= 3.626
STANDARD DEVIATION	= 1.848
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 0.7752
BETA	= 1.2760

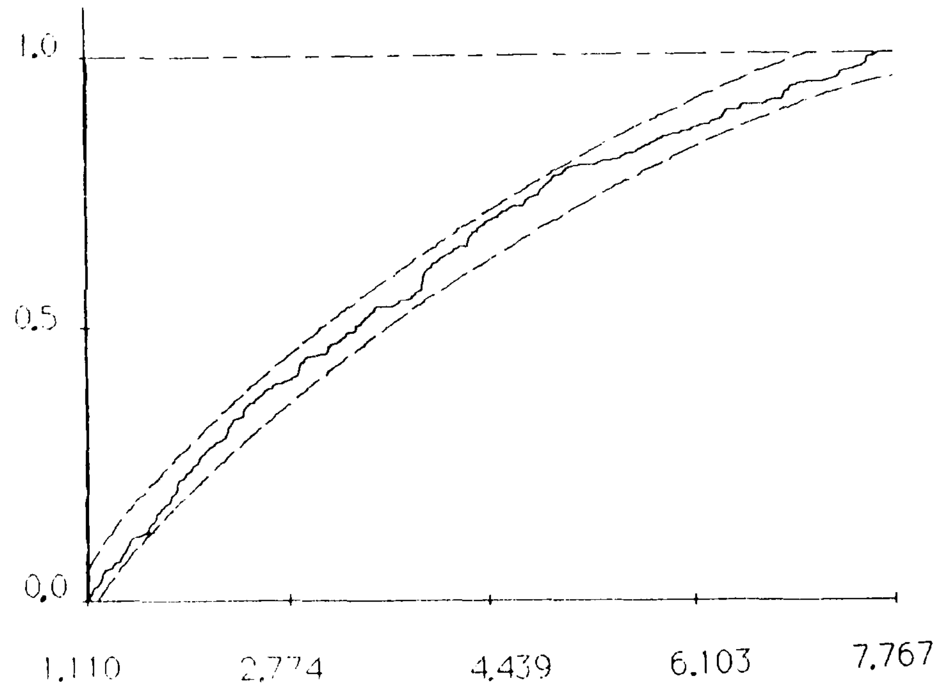

Figure 5 MIC MCC Goodness of Fit Test

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0 1809	1 776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3 773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6557		

SAMPLE STATISTICS:

MEAN = 3.626
STANDARD DEVIATION = 1.848
MINIMUM VALUE = 1.100
MAXIMUM VALUE = 1.767

HYPOTHESIZED DISTRIBUTION: BETA

PARAMETERS:

MEAN = 3.626
STANDARD DEVIATION = 1 848
MINIMUM VALUE = 1.110
MAXIMUM VALUE = 7 767
ALPHA = 0 7752
BETA = 1 2760

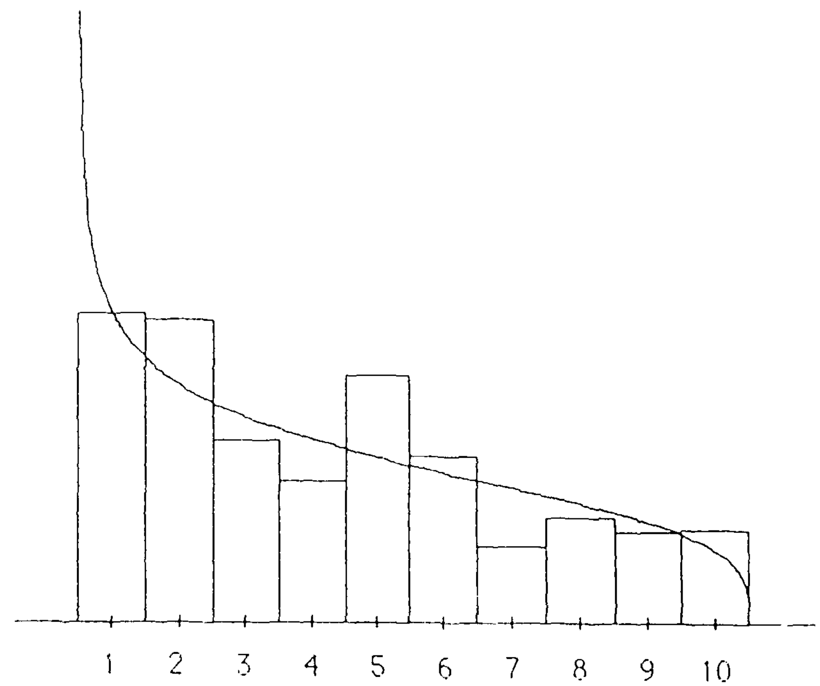

Figure 6. MIC MCC Hypothesized Beta Distribution

MIC MDD Goodness-of-Fit Tests. As shown in Appendix G, none of the ten theoretical distribution adequately fit the MDD data set using the KS test. None of the computed KS test statistics for each of the 10 distributions tested were less than the KS critical value of 0.0435 computed by the AID program. In order to not reject the null hypothesis, the KS test statistic computed from the sample data would have to be less than the critical value. However, the goodness-of-fit test for the lognormal distribution with μ = 1.773 days and σ = 1.307 came the closest to not rejecting the null hypothesis. Additional KS tests were conducted, as displayed in Table 11 in Appendix H, to test additional mean and standard deviation values near 1.773 and 1.307 days respectively. As shown in Table 11, none of the additional parameter sets resulted in a KS test statistic lower than the 0.106 score achieved by the original test for lognormal fit to the data.

As noted in Chapter II, some researchers have determined that lead time data is sometimes so variable that it may not fit familiar theoretical probability distributions, or may shift around in no discernable pattern. In spite of the absence of statistically significant evidence that the MDD data is distributed lognormally with μ = 1.773 and σ = 1.307, no more appropriate probability distribution was found. Therefore, this distribution was used as an input parameter in simulation experiments for MIC MDD. Figure 7 presents the proposed lognormal distribution PDF used to describe the MDD data set. Additionally, a histogram of the actual MDD lead time data is shown to facilitate comparison with the proposed lognormal PDF function.

MIC MFF Goodness-of-Fit Tests. Similar difficulties were experienced when attempting to fit theoretical probability distributions to

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	73	0.0748	0.0748	0.661
2	227	0.2326	0.3074	1.043
3	251	0.2572	0.5645	1.425
4	50	0.0512	0.6158	1.807
5	110	0.1127	0.7285	2.189
6	18	0.0184	0.7469	2.571
7	43	0.0441	0.7910	2.953
8	119	0.1219	0.9129	3.335
9	11	0.0113	0.9242	3.717
10	74	0.0758	1.0000	4.099
	976	CELL WIDTH = 0.382		

SAMPLE STATISTICS:

MEAN = 1.734
STANDARD DEVIATION = 1.040
MINIMUM VALUE = 0.279
MAXIMUM VALUE = 4.099

HYPOTHESIZED DISTRIBUTION LOGNORMAL

PARAMETERS:

MEAN = 1.773
STANDARD DEVIATION = 1.307
ALPHA = 1.428
BETA = 0.6585

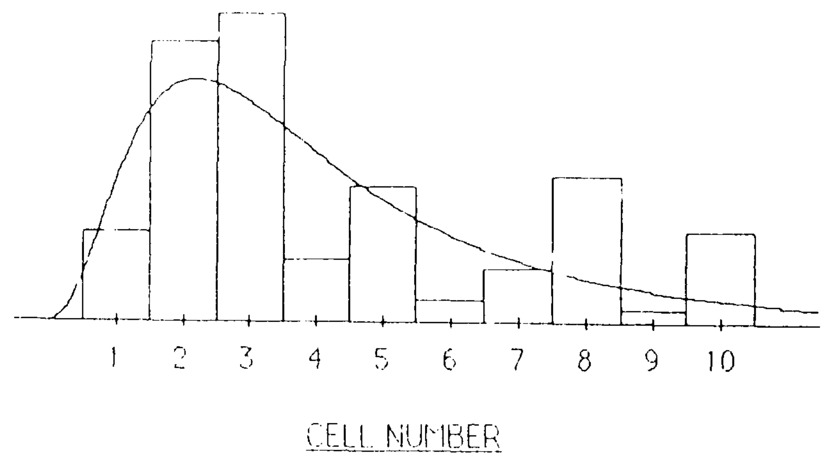

Figure 7. MIC MDD Proposed Lognormal Distribution

the MFF data sample. As Appendix G shows, none of the computed KS test statistics for the 10 theoretical distributions examined were less than the KS critical value of 0.0434 computed by the AID program. The best goodness-of-fit test results were for the lognormal distribution with μ = 1.413 days, σ = 1.088 days, and a KS test statistic of 0.135. As before, additional KS tests were conducted (Table 12 in Appendix H). However, none of these tests resulted in a test statistic lower than the 0.135 score achieved by the original test for lognormal fit to the data. Therefore, since the lognormal test with μ = 1.413 and σ = 1.088 resulted in the lowest overall KS test statistic, and provides the best overall fit to the data of all the tests conducted, this distribution was used as an input parameter in simulation experiments for MIC MFF. Figure 8 presents the proposed theoretical lognormal distribution PDF, shown as the solid curved line, and a histogram of the actual MFF lead time data.

To summarize distribution-fitting efforts outlined in this section, attempts to fit lead time data to theoretical probability distributions resulted in an adequate fit to the beta distribution for MIC MCC data. However, for MICs MDD and MFF, none of the theoretical probability distributions provided adequate fits to lead time data using the KS test. Previous research efforts have determined that lead time data is sometimes so variable that it may not fit familiar theoretical probability distributions, or may shift around in no discernable pattern. Therefore, the theoretical probability distributions shown in Figures 7 and 8 were used for MICs MDD and MFF as the best available estimates of lead time distributions for each of these respective MICs for their simulation experiments presented later in this chapter.

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	84	0.0855	0.0855	0.540
2	286	0.2912	0.3768	0.918
3	281	0.2862	0.6629	1.296
4	28	0.0285	0.6914	1.674
5	106	0.1079	0.7994	2.052
6	43	0.0438	0.8432	2.430
7	30	0.0305	0.8737	2.808
8	77	0.0784	0.9521	3.186
9	26	0.0265	0.9786	3.564
10	21	0.0214	1.0000	3.942
	982			

CELL WIDTH = 0.378

SAMPLE STATISTICS:

MEAN = 1.3790
STANDARD DEVIATION = 0.8834
MINIMUM VALUE = 0.1620
MAXIMUM VALUE = 3.9420

HYPOTHESIZED DISTRIBUTION: LOGNORMAL

PARAMETERS:

MEAN = 1.413
STANDARD DEVIATION = 1.088
ALPHA = 1.119
BETA = 0.6826

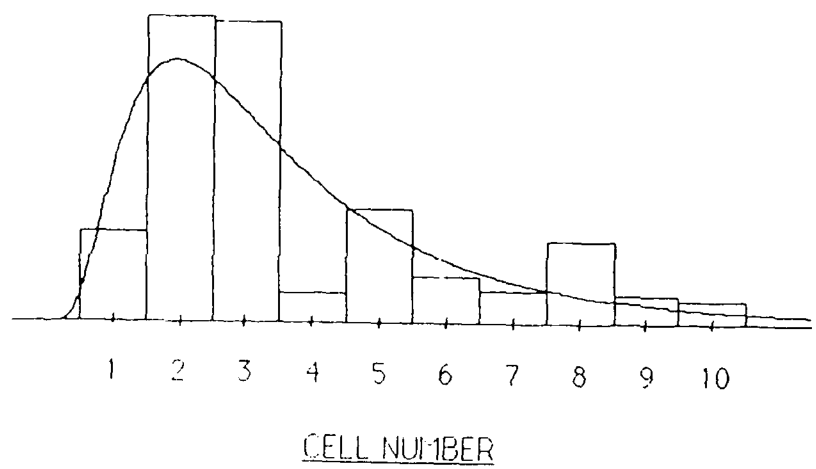

Figure 8. MIC MFF Proposed Lognormal Distribution

Difference Between G402A and Documented Lead Time Data. As discussed in Chapter III, in-transit data was collected from both off-line local issue documents and DD Forms 1348-1A in order to compare the signature receipt time and date with the corresponding clearance time and date from the G402A database. A census of all MIC replenishment transactions for the ten MICs noted in Chapter III was collected from the G402A database for a two month period from 1 December 1988 to 31 January 1989. A random sample of 251 transactions was selected using a spreadsheet-generated random number sampling scheme. Of the 251 transactions selected, 238 were usable, complete transactions with matching start and stop entries. Personnel at OO-ALC/DSMPA then pulled the corresponding documents (either local issue documents or DD Forms 1348-1A) so that the off-line documents could be compared to the data available for the same transaction from the G402A data sample.

Of the 238 off-line documents selected for the sample, only 171 had legible dates of receipt. The time of receipt was not annotated or readable on most of the 171 documents reviewed. Recall that a similar problem with times and dates not being annotated on issue documents was noted by Mr. Clarke in the AFLC in-transit delivery time study outlined earlier in this chapter. In the AFLC study, those documents without the times and dates of receipt annotated on the documents were considered "on-time" deliveries. For the purposes of this study, any document that reflected the same receipt date as indicated on the G402A database was assumed to have cleared the same time as that recorded in the G402A data. In other words, the difference between the two transactions was set equal to zero. Thus, the dates of receipt indicated on the off-line documents was in all cases equal to or less than the date of receipt reflected in the G402A data. The time of receipt for those transactions that showed a document clearance date earlier than the G402A date was set at 1600 hours. This assumed that all documents on a given date would have been signed for at least by 1600 hours or earlier on that day. With the exception of those MICs that operate shifts and receive material after 1600, this time should reasonably reflect the latest time during a given day that a transaction would be receipted for by MIC personnel. However, it should be noted the estimated mean difference presented below probably understates what might be actually observed if the documents accurately reflected the data and time of receipt by MIC personnel.

An estimate of the mean time to clear a transaction, or the difference between G402A-derived lead time and the off-line document-derived lead time is shown in Table 4, as well as other descriptive statistics. The mean difference observed between the G402A lead time values and the off-line document lead time values was 0.744 days, with a standard deviation of 1.847 days. In other words, it took 0.744 days on average to clear a transaction from the Depot Maintenance [illegible]2A database after MIC personnel physically received and signed for a replenishment order.

Figure 9 indicates that the paired difference data for the 171 transactions may not be normally distributed. The data appears to be strongly skewed to the right. Additionally, the frequency distribution table of the data presented in Appendix I shows that 90% of the 171 observations differed by 1 day or less.

Table 4. Observed Difference Descriptive Statistics

Mean Difference	=	0.744
Standard Deviation of Differences	=	1.847
Minimum Difference	=	0.000
Maximum Difference	=	12.660
Kurtosis	=	19.855
Skewness	=	4.036

The computed level of skewness listed in Table 4 is 4.036, indicating that there is a significant number of data points that lie to the right of the mean (21:72). Kurtosis measures whether a distribution of data has "heavy tails," or whether the data contains some values that are extremely distant from the mean relative to most other values in the data set (21:72). The computed kurtosis statistic was 19.855, a relatively significant indication of non-normality. The final indication of non-normality of the difference data can be seen from the box plot of the data shown in Figure 10: 75% of the data points lie within the interval from 0 to 0.685. The small horizontal line connected to the box by a small vertical line represents the 90th percentile of the data. Finally, the circles near and above the 90th percentile line are the 17 data points that lie above the 90th percentile, indicating a significant number of outlier data points exist in the data. Visual inspection of the histogram and box plot, and the computed skewness and kurtosis statistics strongly support the assumption that the observed difference data are not normally distributed.

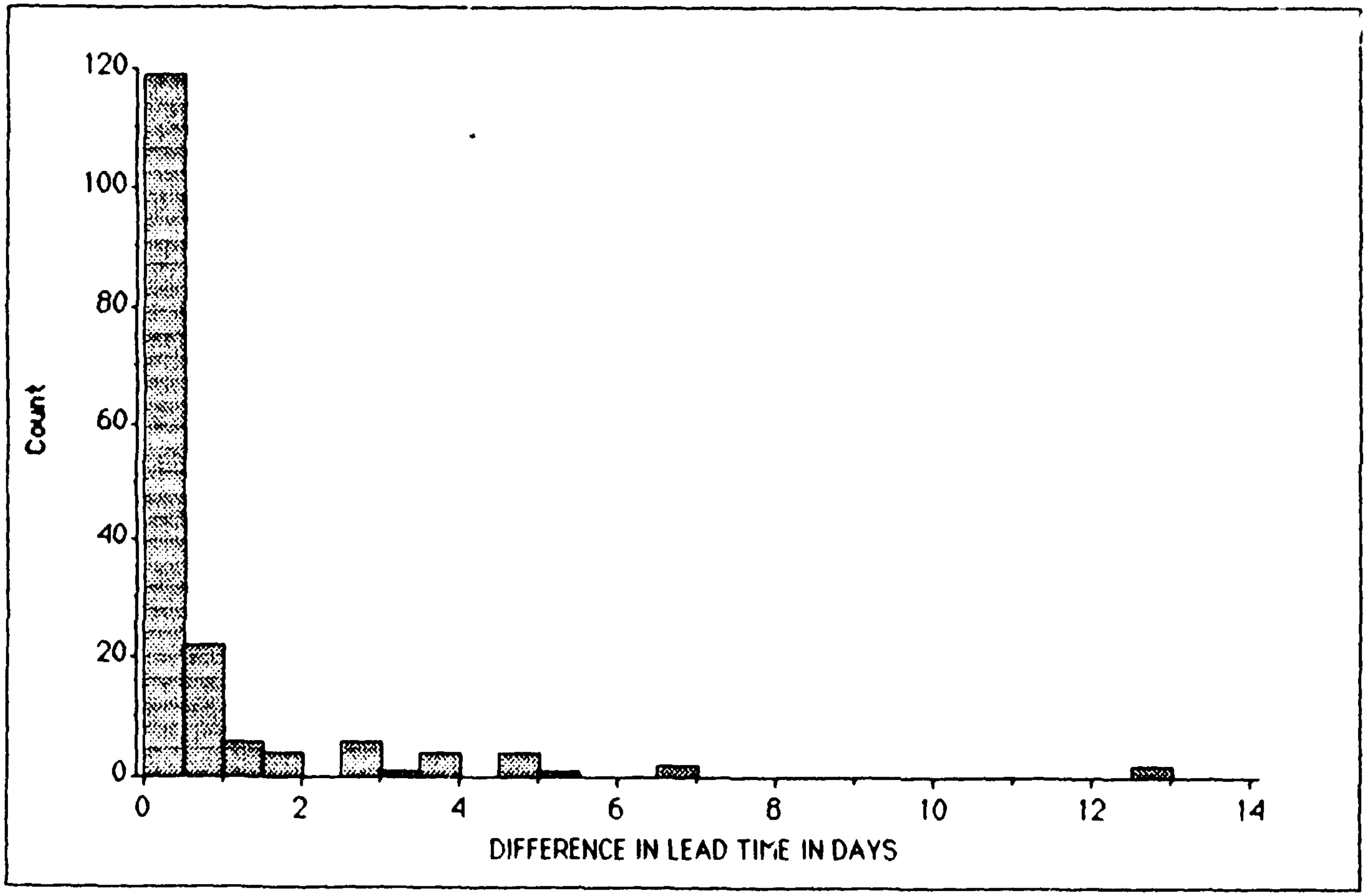

Figure 9. Frequency Distribution Histogram of Observed Difference Data

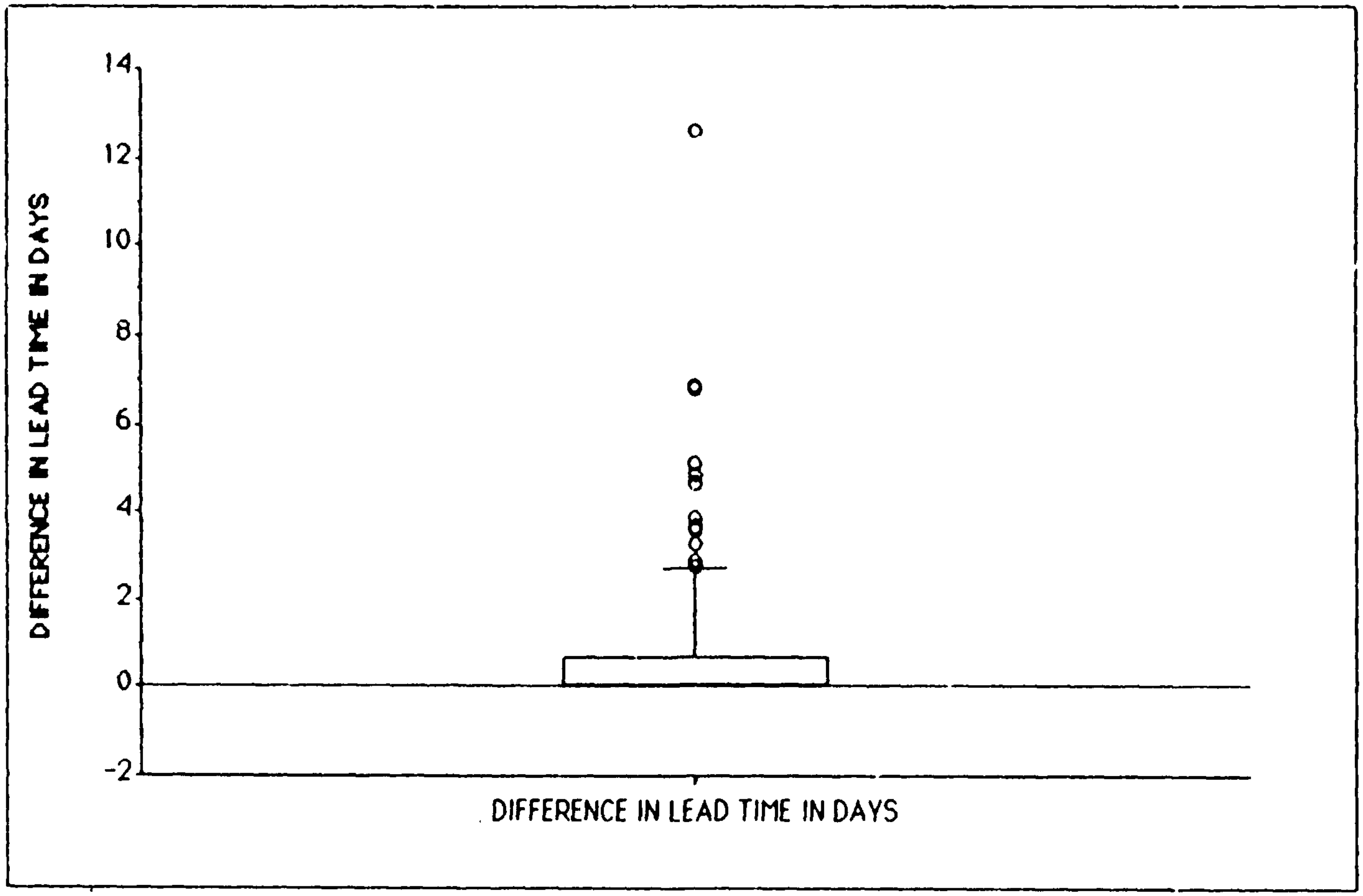

Figure 10. Box Plot of Observed Difference Data

In light of this finding, the application of the parametric paired t-test is not appropriate. This test requires that the differences between two samples be approximately normally distributed. The nonparametric equivalent to the paired difference t-test, the Wilcoxon Signed Rank test, was therefore used to test whether a statistically significant difference existed between the paired off-line document times and the G402A database times. The Wilcoxon Signed Rank test does not require normality of the differences, but does require that the paired observations be independent from one another (21:187). The random sampling scheme outlined in Chapter III used to select the paired transactions reasonably assures that the paired observations in the sample are independent. The null hypothesis was that the mean difference between the the off-line document data and the G402A data was 0, versus the alternative hypothesis that the mean difference between the two samples is significantly different from 0. At an α of 0.05, the test statistic was computed as 689 using the SAS statistical analysis computer package. The significance of this test statistic was 0.0001. The null hypothesis is strongly rejected, and it can be concluded that the mean difference between the documented lead times and the G402A lead times is significantly different from 0.

Thus, the mean difference of 0.744 days was used to estimate the amount of time between signature receipt and clearance of the document on the G402A data system. To correct for this time lag, in the simulation 0.744 days were subtracted from delivery lead time values generated according to hypothesized probability distributions.

Table 5 shows the hypothesized reductions in mean delivery lead times (based on Table 3) that would result from subtracting the estimated

Table 5. Revised Mean In-Transit Delivery Time Data

MIC Identifier	Month: December	January	February	March	April	May
MCC	5.849	2.806	4.035	3.107	3.797	3.490
MDD	2.713	1.091	0.906	1.310	1.075	1.647
MFF	2.251	1.080	0.927	0.603	0.781	1.182
MBB	3.878	2.670	1.948	1.650	1.460	1.590
MHH	5.408	2.787	2.799	3.273	3.136	3.015
MLL	2.258	0.856	1.198	1.066	2.410	1.572

0.744 days required to clear a transaction from the G402A database. It is interesting to note that when the 0.744 days estimated time to clear a transaction is subtracted from empirical mean delivery in-transit times presented in Table 3, approximately 36% of the monthly averages fall below HQ AFLC's 1.5 day delivery time standard. However, based on the G402A lead time data, even after subtracting out the lag time for clearing the transaction, nearly 64% of the monthly delivery time averages still exceed HQ AFLC delivery time standards. The next section describes how the empirical in-transit delivery time data were incorporated into the simulation experimental design.

Simulation of In-Transit Delivery Time Impact

In accordance with the simulation experimental design described in Chapter III, simulation experiments were conducted with varying levels of β

values (Days Between Requests, DBR), λ values (Units Per Request, UPR), O&ST mean and standard deviation measures, and theoretical probability distributions of O&ST. Observed O&ST mean and and standard deviation values, and appropriately "fitting" theoretical probability distributions discussed earlier in this chapter were used to generate random in-transit delivery times (O&ST values). The 0.744 days average difference between signature receipt and G402A clearance of the transaction was subtracted out from O&ST values generated in simulation experiments. Resulting performance measures of LIFR, UFR, average number of backorder-days per year and backordered units per year, and average on-hand inventory levels in units were collected to describe the impact that various demand and O&ST parameters have on MIC inventory stockage performance. Simulation results and analyses are presented, by MIC, in the following sections.

<u>MIC MCC Simulated Inventory Performance</u>. The resulting simulated inventory performance for MIC MCC is illustrated in Table 6. The λ value was fixed at 2 units per request for MIC MCC simulations. The O&ST, or in-transit delivery times, were drawn from a beta distribution where μ = 3.626 days, σ = 1.848 days, α = 0.7752, β = 1.276, a minimum of 1.11 days, and a maximum of 7.767 days as discussed previously.

The average number of units requested during each simulated six month stockage period decreased significantly as the β values increased. The LIFR and UFR decrease significantly as the β increases. This is probably due to the 15/7 inventory policy, which does not perform well in terms of LIFR and UFR for infrequently demanded items. The average on-hand inventory levels for each value of β indicate that items with higher frequency of demand will be stocked at higher levels and available in the

Table 6. MIC MCC Simulated Performance Measures, λ = 2, and Beta-Distributed In-Transit Delivery Times

DBR (β)	Average Units Requested	LIFR (%)	UFR (%)	Backorder-Days (per year)	Average Backorders (units/year)	Average On-Hand Inventory
3	126.0	95.6	96.53	10.67	6.5	7.14
12	31.9	84.3	89.58	8.43	6.0	2.61
110	3.8	0.0	45.83	9.71	4.7	0.97

MIC more often than those items with lower frequency of demand. For example, an item with β equal to 3 will have an average on-hand inventory of 7.14 units, which as indicated by LIFR measures is adequate to fully meet demand 95.6% of the time. An item with β equal to 110, on the other hand, displays significantly degraded performance. The average on-hand inventory for an item with β = 110 is 0.97 units, which results in a 0.0% LIFR. The 0.0% LIFR implies that no demand was filled to the full amount requested when β = 110. The average on-hand inventory was only able to partially fill 45.83% of the demands with on-hand stock in the MIC, as indicated by the UFR.

The average number of backorder-days per year (or the total number of days required for backorders to be filled), and the average number of backordered units per year are influenced by a MIC stockage policy that does not "adequately allow for volume or variability of demands" or when the O&ST from DS of replenishment issues is high (as shown in Table 5 for MCC), according to McBride (22:67). It is interesting to note that while the LIFR and UFR are much higher for frequently demanded items in MIC MCC, their average number of backorder-days and backordered units are higher than for less frequently demanded items. Table 6 represents a baseline for future inventory performance comparisons. The combination of high O&ST values with the 15/7 inventory policy (which relies heavily on expedient on-base deliveries) results in less than desirable performance except for items demanded extremely frequently.

MIC MDD Simulated Inventory Performance. Table 7 shows the simulated inventory performance for MIC MDD. The λ value was Poisson-distributed with a mean of 6 units per request for MIC MDD simulations. The O&ST in this case were drawn from a lognormal distribution with μ = 1.773 days and σ = 1.307 days.

Table 7. MIC MDD Simulated Performance Measures, λ = 6, and Lognormally-Distributed In-Transit Delivery Times

DBR (β)	Average Units Requested	LIFR (%)	UFR (%)	Backorder-Days (per year)	Average Backorders (units/year)	Average On-Hand Inventory
3	378.1	97.7	98.58	7.39	3.8	22.99
28	40.6	28.1	56.73	42.45	10.6	3.65
110	10.4	8.3	33.44	15.24	4.5	1.56

Similar to the results seen for MIC MCC, the average number of units requested per six month simulated stockage period decreases significantly as the β values increase, reflecting that the less frequent demands (110 DBR) result in fewer overall units requested. LIFR and UFR decrease significantly as the β increases. This is once again attributable to the 15/7 inventory policy, which does not perform well in terms of LIFR and UFR for infrequently demanded items. The average on-hand inventory levels for each β value indicate that more frequently demanded items will be stocked at higher levels and available in the MIC more often than less frequently demanded items.

Compared to the MIC MCC results, the lognormal lead times and $\lambda = 6$ result in a higher numbers of backorder-days per year and backordered units per year for the medium and high β values. In the medium DBR range, the resulting average on-hand inventory of 3.65 units cannot adequately meet demands averaging 6 UPR, as indicated by the lower LIFR, UFR, and degraded backorder performance measures. Again, as noted by McBride, relatively long O&ST values, as well as the 15/7 day stockage policy are unable to provide adequate support for higher volume (greater UPR) or variable demands (22:67).

<u>MIC MFF Simulated Inventory Performance</u>. The resulting simulated inventory performance for MIC MFF is shown in Table 8. The λ value was Poisson, and fixed at 9 units per request for MIC MFF simulations. The O&ST values were drawn from a lognormal distribution described by $\mu = 1.413$ days and $\sigma = 1.088$ days.

Similar to the results seen for MICs MCC and MDD, the average number of units requested per six month simulated stockage period decreases significantly as the β values increase. LIFR and UFR also decrease significantly as the β increases. This is once again attributed to the higher UPR and the 15/7 inventory policy. Likewise, average on-hand inventory levels for each value of β indicate that more frequently demanded items are stocked at higher levels and available in the MIC more often than less frequently demanded items. The average on-hand inventory

Table 8. MIC MFF Simulated Performance Measures, λ = 9, and Lognormally-Distributed In-Transit Delivery Times

DBR (β)	Average Units Requested	LIFR (%)	UFR (%)	Backorder-Days (per year)	Average Backorders (units/year)	Average On-Hand Inventory
9	191.4	83.9	92.62	21.85	7.7	13.81
22	81.2	34.5	67.58	48.40	12.5	6.72
110	15.8	2.5	26.24	18.07	4.6	2.07

for an item with β = 110 is 2.07 units, which results in a 2.5% LIFR, and is only able to fill 26.24% of the demands (either fully or partially) with on-hand stock in the MIC.

The higher λ value of 9 UPR (as compared to MIC MDD) results in a higher numbers of backorder-days per year and backordered units per year for the medium and high β values. In the medium DBR range, the average on-hand inventory of 6.72 units is inadequate to satisfy demands averaging 9 UPR, as indicated by the lower LIFR, UFR, and degraded backorder performance measures. A similar situation with inadequate average on-hand levels existed for MIC MDD as well. Again, as noted by McBride, long O&ST values, as well as the 15/7 day stockage policy are unable to provide adequate support for higher volume or variable demands (22:67). The problem is exacerbated in the case of MFF due to the significantly higher UPR of 9, relative to MIC MDD.

Intermediate Summary

Each of the MICs tested in the simulation experiments described above provided varying levels of inventory support, depending upon the β, λ, and

O&ST parameters used to characterize the inventory environment in each respective MIC. For frequently demanded items (those with low β values), results indicated that the 95% LIFR goal could only be reached in two of the cases. These cases were for MIC MCC with a β of 3 days, and for MIC MDD with a β of 3 days.

In all cases tested, as the β value increased, poorer fill rate performance resulted. Additionally, average on-hand inventory decreased in all cases as well. The average number of backorder-days and backordered units were much higher for the medium DBR range items for MICs MDD and MFF. This indicates that λ, or the units per request, was also an influential factor in the inventory system's performance. Therefore, the 15/7 day inventory policy, the λ value, as well as the proposed O&ST parameters tested are important contributors to degraded inventory performance (especially for medium and low frequency of demand items). The focus of this study remains, however, the impact of in-transit delivery times upon inventory system performance. The next section examines several statistical process control tools that may be useful in managing in-transit delivery times.

<u>Application of Quality Control Concepts and Tools</u>

This section examines the applicability of quality control, continuous process improvement and variance reduction concepts. Several of the tools, techniques and concepts for improving the quality of a process such as the in-transit delivery of MIC replenishment orders at OO-ALC were described in Chapters II and III. The application of SPC and control charts is the main tool examined in this analysis. The primary objectives of this analysis were to examine the feasibility of using SPC and control charts to identify potential areas for reducing the overall mean and variance of in-transit delivery time, and to show show some of the delivery time trends that merit the attention of a PAT team to resolve and improve the overall process.

Elementary SPC Chart Analysis Overview. As discussed previously, a control chart provides a graphic comparison of process performance data to computed "control limits" that are drawn as upper and lower boundary lines on the chart (18:228). When the actual variation of a process exceeds the control limits, it is a signal that assignable causes of variation other than random variation have entered into the process. These assignable causes should be investigated, corrective actions taken, and the process modified to reduce the variation (18:290). Opportunities to continuously improve the process under analysis may be identified and exploited in this way.

There are four basic types of control charts noted by Juran and Gyrna, though many variations of these four basic types of tools have been developed (18:290). The $\overline{X}$ (or "X-bar") chart is based on averages of measurements in a sample of data, and is used to examine the average measures of the "aim," or centering of a process measurement (18:290). R-charts display the range (or the difference between the highest and lowest value) within a sample of measurements, and are used to measure the variability around the aim of the process. A third basic type of control chart is the c-chart. The c-chart is designed to examine the number of items within a sample that are defective, or unacceptable when evaluated against some criteria of acceptable quality (18:290). For instance, when analyzing the in-transit delivery process, a "defective" in-transit delivery would be one with a lead time exceeding 1.5 days. Finally, the fourth basic type of control chart is the p-chart, which tracks the percent considered defective within a given sample of measurements (18:290). Examples of each of these differing control charts are discussed in a later section of this analysis.

Juran and Gryna outline six basic steps that can be followed to set up control charts to analyze a process (18:336-338). First, choose the characteristic to be scrutinized and charted. The characteristic should be a process variable that contributes significantly to the end product's quality. The second step is to select the type or types of control charts that provide the necessary analysis capabilities. Third, decide the "centerline," or process aim to be charted, and the basis for calculating the control limits (18:336). Averages based on actual past data, or desired values can be used to establish the centerline. The fourth step is to choose a "rational subgroup" to analyze (18:337). Each point on the chart should represent a subgroup, or sample consisting of several units of a product that are similar in some way. For instance, the data within a subgroup may all be measurements from a certain machine or work area, or may be from a given day or week. The fifth step is to develop a system for collecting the necessary process data required to diagnose and improve the process. If the control charts are to be used as day-to-day tools in the shops and work areas, they must be simple and convenient to use. The measurement methods used to provide the necessary data should be as simple as possible, made error free, with prompt and reliable process data collection as the end result. The sixth step outlined by Juran and Gryna is to calculate the control limits, and to provide specific instructions on how to interpret the results. Also, the actions to be taken by personnel involved with the process to address problems and opportunities for continuous improvement should be specifically outlined as part of this final step (18:337).

The characteristic examined in this analysis is the in-transit delivery time. For illustrative purposes, only one MIC sample for one month was analyzed to show the applicability of control charts as a process improvement tool. Empirical measures of mean and standard deviation of in-transit delivery times presented earlier in this chapter indicated that MIC MCC generally experienced higher mean lead times than the other MICs in this study. Figure 11 displays the mean and standard deviation measures of delivery times observed for MIC MCC over the six month study period. It can be seen that February resulted in the highest relative measures of lead time mean and standard deviation, with the exception of the values from December. Recall that December data was believed to be heavily influenced by holidays, leaves, and production draw-downs, and therefore may not be truly reflective of the in-transit delivery process. Therefore, February data was chosen as the focus for the control chart demonstration.

The observed lead time data sample from MIC MCC for February consisted of 242 data points. All four of the control charts described earlier are developed and reviewed below. The center lines for all the charts are averages computed from the sample data. The rational subgroup (or sample size) was set at 11 data points per sample so that 22 total samples would be included in the analysis. The 242 data points were sorted in ascending order of transaction start time and date. In other words, the transactions were sorted in the order in which the D033 notified the G402A data system that the asset was in-transit. Again, the rational subgroup of 11 data points per sample was chosen more for convenience and illustrative purposes so that

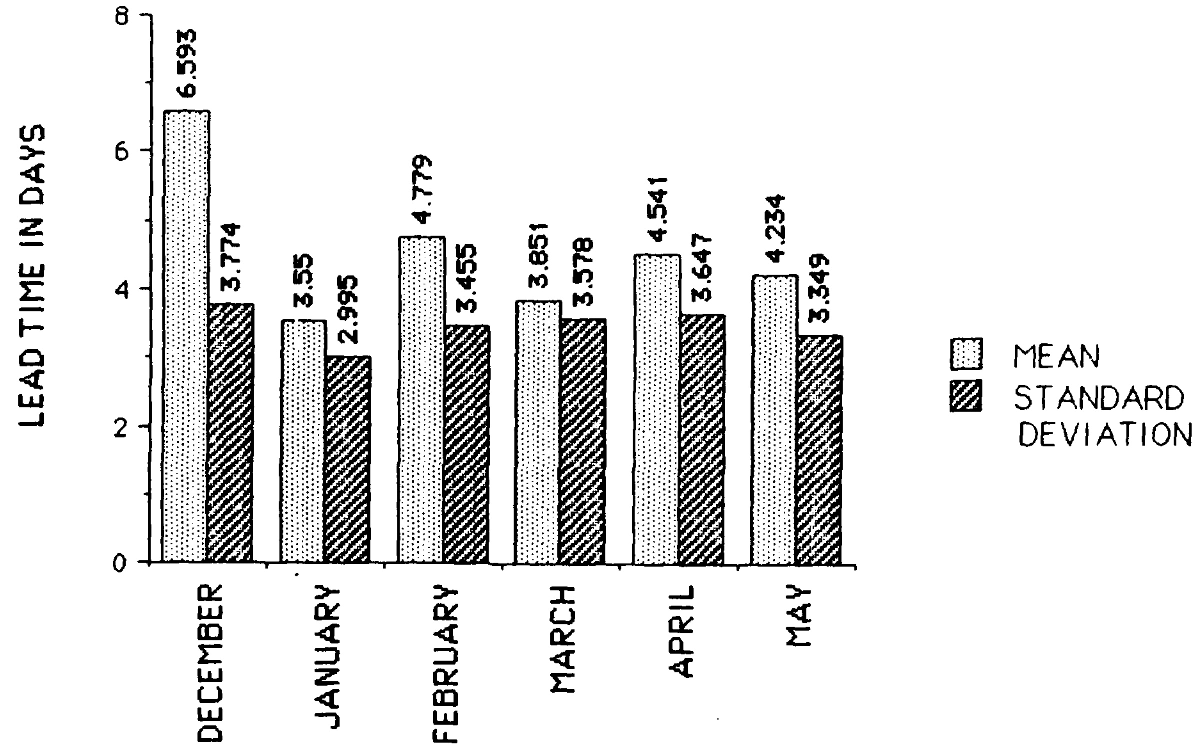

Figure11. MIC MCC Mean and Standard Deviation of Lead Time Values for December 1988 to May 1989

22 samples of 11 data points each could be considered in this analysis. A PAT would evaluate and assign a rational subgrouping of data to meet their particular circumstances and analysis purposes. The February MCC data points, sorted into 22 samples can be seen in Appendix J, along with the computed $\bar{X}$, R, number defective and percent defective values. Each of the four types of control charts using the MIC MCC February data sample are described in the following sections.

<u>X-Bar Chart Analysis.</u> Figure 12 displays the X-bar control chart for the February MCC in-transit delivery time data. The Upper Control Limit (UCL) and Lower Control Limit (LCL) were computed using the following formulas:

$$UCL = \bar{\bar{X}} + A_2(\bar{R}) \tag{4}$$

$$LCL = \bar{\bar{X}} - A_2(\bar{R}) \tag{5}$$

where

$\bar{\bar{X}}$ = Grand average, or average of the sample averages

$\bar{R}$ = Average of the sample ranges

A_2 = Constant for computing $\bar{X}$ control limits (18:291)

The A_2 constant can be found in Table I of the appendix of Juran and Gryna's <u>Quality Planning and Analysis</u> (18:611). Tables of these constants are widely used and are commonly found in any text or handbook on quality control analysis. From this table, the A_2 value for a sample size of 11 observations is 0.285. The $\bar{\bar{X}}$ = 4.779, and the $\bar{R}$ value = 8.299. The resulting UCL using Eq (4) was 7.145, and the resulting LCL using Eq (5) was 2.414. The UCL and LCL, $\bar{\bar{X}}$ centerline, and 22 sample data points are shown in Figure 12.

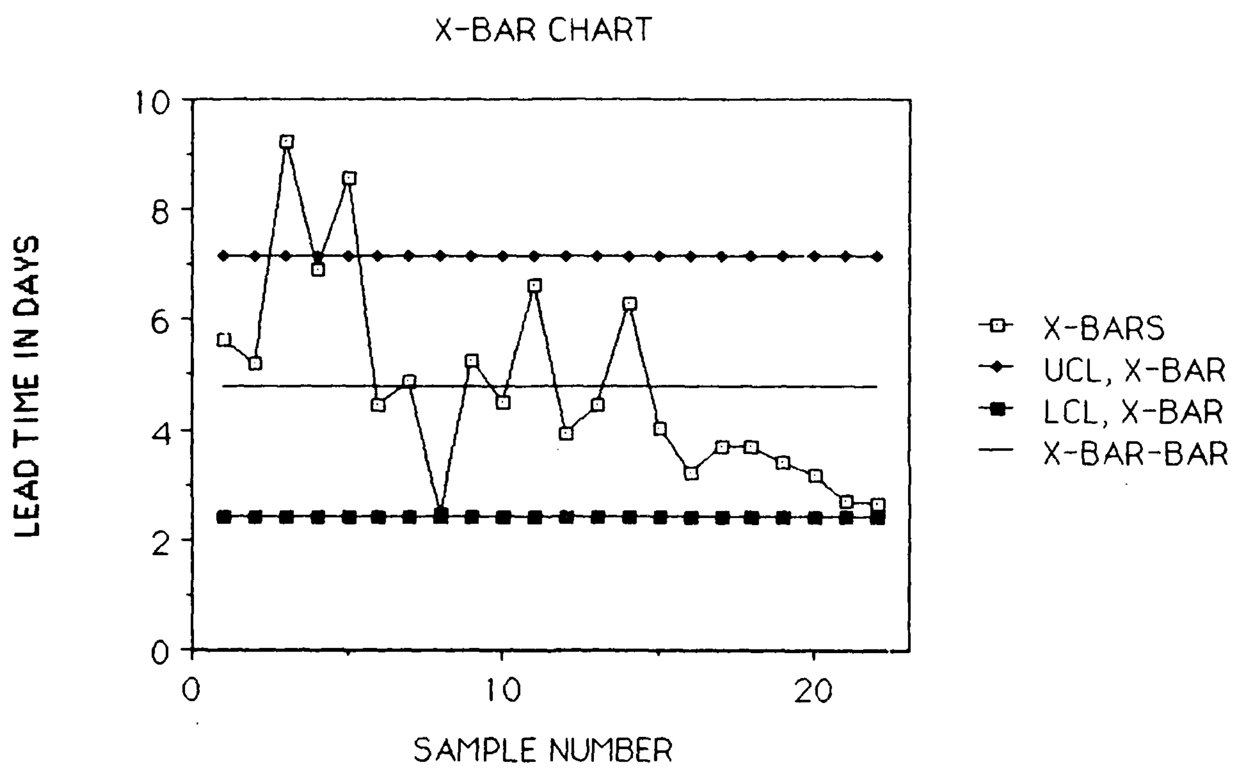

Figure 12. X-Bar Chart for MIC MCC Lead Time Data

The process as shown in the X-bar control chart is highly variable, with the third and fifth sample data points exceeding the UCL of 7.145 days. Also, the fourth sample data point is just below the UCL. These samples include lead times that can be strongly considered as having assignable causes of variation, and should be investigated so that the causes can be determined, corrected, and lessons learned applied to continuously improving the process. Also, the "sawtooth" pattern of data points for samples 6 through 15 highlight additional variation around the mean centerline value. Even though these samples are within the control limits, process improvement may be possible if the assignable causes for this "up-and-down" variation can be determined and corrected. Again, the lessons learned may improve the overall delivery process. Finally, the last 8 samples displayed on the chart indicate a strong trend in decreasing lead times as the process begins to approach the LCL of 2.414 days. Members of a PAT could investigate why the process is apparently improving in such a drastic manner. If assignable causes could be determined, the delivery process may be improved further. Thus, both extremely high and extremely low in-transit delivery times should be investigated, assignable causes determined, and the process improved so that a more consistent and better performing delivery capability is forged.

<u>R-Chart Analysis.</u> Figure 13 displays the resulting R-chart for the February MCC in-transit delivery lead time data. The Upper Control Limit (UCL) and Lower Control Limit (LCL) were computed using the following formulas:

$$UCL = D_4(\bar{R}) \tag{6}$$

$$LCL = D_3(\bar{R}) \tag{7}$$

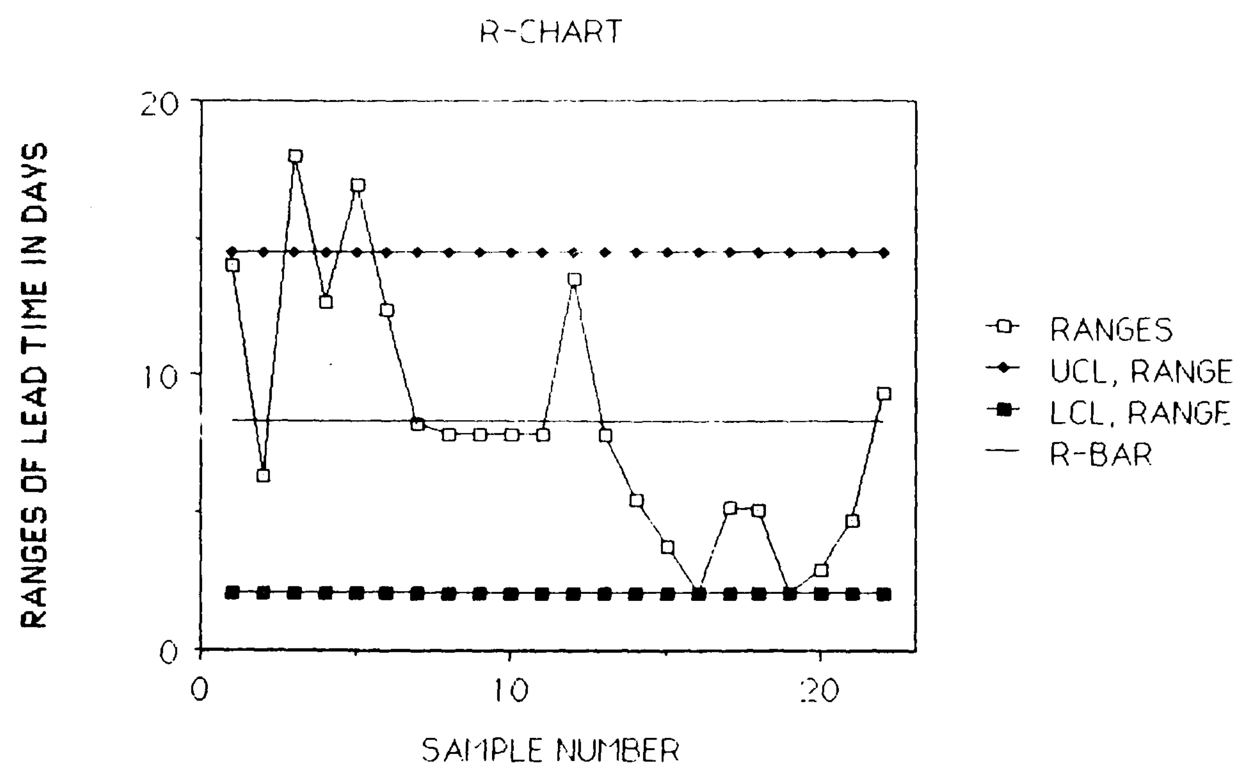

Figure 13. R-Chart for MIC MCC Lead Time Data

where

$\bar{R}$ = Average of the sample ranges

D_4, D_3 = Constants for computing R-chart control limits (18:291)

The D_4 and D_3 constants can also be found in Table I of the appendix of Juran and Gryna's Quality Planning and Analysis (18:611). From this table, D_4 for a sample size of 11 observations per sample is 1.744, and D_3 for the same sample size is 0.256. As before, $\bar{R}$ = 8.299. The UCL using Eq (6) was 14.473 days, and the LCL applying Eq (7) was 2.125 days. The UCL and LCL, $\bar{R}$ centerline, and 22 sample data points are shown in Figure 13.

The process as depicted in the R-chart is also highly variable, with a sawtooth pattern appearing in the first seven data points. Additionally, the third and fifth sample data points exceed the UCL of 14.473 days. These samples include delivery time range values that can be strongly considered as having assignable causes of variation, and should be investigated so that the causes can be determined, corrected, and lessons learned applied to continuously improving the process. Samples 12 through 16 exhibit a dramatic decrease in range over time, approaching the LCL of 2.125 days. If investigated, and assignable causes are found, process improvement opportunities may arise. Finally, the last 3 samples displayed on the chart indicate a strong trend in increasing delivery time range values. Members of a PAT could investigate why the ranges are oscillating in such a drastic manner. Again, both extremely high and extremely low in-transit delivery time range values should be investigated, assignable causes determined, and the process improved so that a less variable and better performing delivery capability is developed.

Number of Defects (c-Chart) Analysis. Figure 14 displays the c-chart for the February MCC in-transit delivery time data. The criteria for a "defective" delivery was set at 1.5 days. Any in-transit delivery time that exceeded 1.5 days was counted as a defect in accordance with the 1.5 day/12-working hour delivery time criteria discussed in Chapter I. The centerline for the c-chart is represented by $\bar{c}$, or "c-bar." The following formula is used to compute c-bar:

$$\bar{c} = (a/b) \tag{8}$$

where

$\bar{c}$ = Average number of defects per sample

a = Total number of defects in overall sample, or 220

b = Number of samples, or 22 (adapted from 18:344)

The resulting c-bar computed from Eq (8) was 10. The Upper Control Limit (UCL) and Lower Control Limit (LCL) were computed using the following formulas:

$$UCL = \bar{c} + 3\,(\,\bar{c}\,)^{1/2} \tag{9}$$

$$LCL = \bar{c} - 3\,(\,\bar{c}\,)^{1/2} \tag{10}$$

where

$\bar{c}$ = Average number of defects per sample (18:344)

The UCL using Eq (9) was 19.487 defective units, and the LCL applying Eq (10) was 0.513 defective units. With only 11 data points in a sample, the UCL of 19.487 is of little analytical value, and the LCL was effectively equal to 0. Because of the high c-bar value relative to the sample size, the process control limits computed based on the sample data indicate that the process would be considered in control if all 11 deliveries in a given sample were defective (greater than 1.5 days).

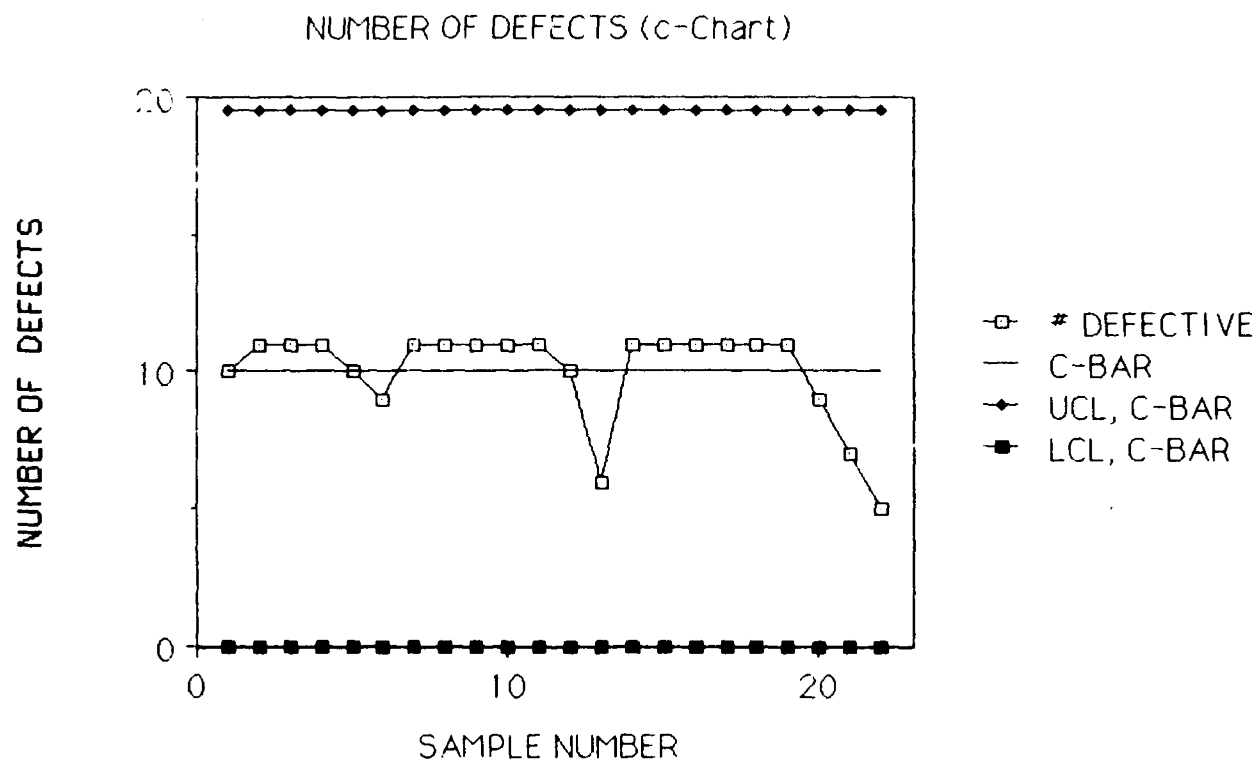

Figure 14. Number of Defects (c-Chart) for MIC MCC Lead Time Data

Since 14 of the samples each contained 11 "defective" lead time values, c-chart analysis in this case does little more than to highlight that the 1.5 day delivery standard is much too stringent for the current delivery process capability. However, a PAT might benefit by looking more closely at the last three samples on the chart. There is a sharp decline in the number of defective (or late deliveries) at these points. This decline corresponds to the decreasing delivery time trend indicated in the last four data points portrayed in the x-bar chart shown in Figure 12. The last four samples of lead times should be scrutinized and exploited for delivery process improvement opportunities.

Percent Defective (p-Chart) Analysis. Figure 15 displays the p-chart for the February MCC in-transit delivery time data. The criteria for a "defective" delivery was set at 1.5 days. Any in-transit delivery time exceeding 1.5 days was counted as a defect. The centerline for the p-chart is represented by $\bar{p}$, or "p-bar." The following formula is used to compute p-bar:

$$\bar{p} = (a/b) \qquad (11)$$

where

$\bar{p}$ = Average fraction defective per sample

a = Total number of defects in overall sample, or 220

b = Total number of items in sample, or 242 (adapted from 18:339)

The p-bar computed from Eq (11) was 0.909, or 90.9% defective. The Upper Control Limit (UCL) and Lower Control Limit (LCL) were computed using the following formulas:

$$UCL = \bar{p} + 3\,((\bar{p}(1 - \bar{p})/\bar{n}))^{1/2} \qquad (12)$$

$$LCL = \bar{p} - 3\,((\bar{p}(1 - \bar{p})/\bar{n}))^{1/2} \qquad (13)$$

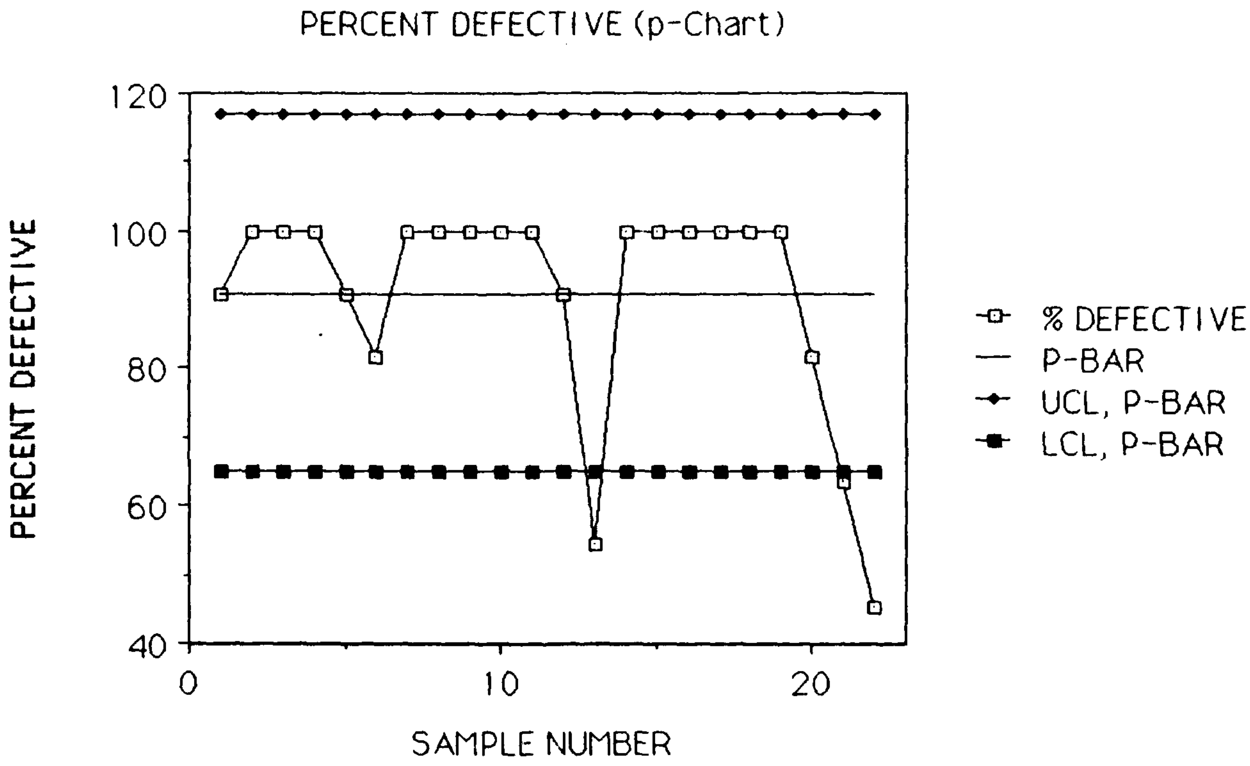

Figure 15. Percent Defective (p-Chart) for MIC MCC Lead Time Data

where

$\bar{p}$ = Average number of defects per sample

$\bar{n}$ = Average number of items in a sample, or 11 (18:344)

The UCL using Eq (12) was 116.991% defective, and the LCL applying Eq (13) was 64.909% defective. As was seen with the c-chart outlined earlier, the UCL of 116.991% is of little analytical value. The process control limits computed based on the sample data indicate that the process would still be within the control limits if over 100% of the deliveries were defective (greater than 1.5 days).

As indicated for the c-chart, p-chart analysis does little more than to highlight that the current delivery process cannot meet the desired capability standard of 1.5 days delivery in-transit time. As shown in Figure 15, 14 of the 22 samples are 100% defective with respect to the 1.5 day delivery criteria. However, process improvement opportunities may be available by looking more closely at sample point 13, and sample points 20, 21 and 22. These points display a sharp drop in the percentage defective deliveries, indicating significantly improved delivery performance. This decrease in percentage defective is matched by a corresponding decline in the number of defects on the c-chart in Figure 15, and a decrease in lead time sample means on the x-bar chart in Figure 12. Once again, these declining lead time trends mean that assignable causes may be detectable, and applicable to improving the overall delivery process capability.

<u>Applicability of Continuous Process Improvement Principles.</u> In the preceding control chart analysis of lead time data, the process does not appear to be "in control" when evaluated in light of the 1.5 day delivery time standard. The reader may be concerned that applying continuous process

improvement principles such as SPC, variance reduction, QP4 and PAT the concepts are not feasible or applicable for the MIC replenishment delivery process if it is indeed "out of control." However, as Juran and Gryna point out:

> In practice, the original control-chart analysis will often show the process to be out of statistical control (It may or may not be meeting product specifications). However, an investigation may show that the causes cannot be <u>economically</u> eliminated from a process. Strictly speaking, a process capability prediction should not be made until a process is in statistical control. However, some comparison of capability to product tolerances [or desired target values, such as 1.5 day delivery lead times] must be made. The danger in delaying the analysis is that the assignable causes may never be eliminated from the process, and the indecision will thereby prolong the interdepartmental bickering on whether 'the tolerance is too tight' or 'manufacturing [is] too careless.' (18:295)

In other words, the delivery process must be confronted, analyzed and continuously improved until the desired capability is obtained, regardless of the perceived difficulties or systematic problems that appear to block the path to continuous process improvement. The principles of QP4, variance reduction, and the formation of a PAT composed of MA and DS personnel involved with the delivery process at OO-ALC (and at the other ALCs as well) may be the only means to effectively improve the process capability.

The biggest hurdle to implementing SPC and other quality control tools and techniques in improving the delivery process is that the current in-transit delivery time data collection methods are inadequate. The researcher has spent over three months to collect, transform and analyze data from the G402A database and off-line issue documents. The data was nearly three months old before any earnest analysis was accomplished. This is not conducive to the day-to-day analysis and control of the delivery process that would be required to highlight assignable causes of variation as they occur, and to address problems or opportunities for improvement. Currently, the ALCs have no system to collect the needed lead time data in a form that is accurate and promptly available to the members of a PAT to effectively analyze the process.

Additionally, the reliability of the data would be improved if the data was available from an automated system, such as the SC&D and DCR systems discussed earlier. It was shown that a significant difference exists between the lead times currently maintained on the G402A and the lead times derived from local issue documents, perhaps by as much as 0.744 days on average. Also, the in-transit delivery time data are not aggregated or stratified to measure the different components that contribute to the overall lead time (or order cycle time) between order shipment from DS to order receipt by MA, as described by Stock and Lambert, and Tersine. It would be much more useful if data were available measuring the amount of time in-transit material spends at different points in the delivery process. For example, the T4 (goods transit time from supplier) and T5 (in-house goods preparation time by the receiving organization) lead time components shown in Figure 1 and described in Eq (1) would yield valuable information in reducing excessive delivery times if accurately measured. More effective analysis in identifying where the "logjams" or "bottlenecks" are in the process, and improving the overall process would then be possible. However, evaluating only the time between when an order is initiated by DS and finally received at the MIC leaves many questions unanswered about what has happened to a given in-transit order within that time period. An automated system such as those described earlier in this chapter is the only practical way to collect, maintain, and provide the required transaction data on a prompt, usable and reliable basis.

Nonetheless, in spite of the inadequate measures of lead time available with current data collection methods, the application of quality control principles may be the only means available to address the current delivery system's inability to meet the desired 1.5 days performance criterion. The consequences of inaction are that the process may never be improved to the point of being capable of achieving the desired capability.

Any PAT team applying many of the quality control, QP4 and variance reduction principles and tools described in Chapter II and III (and discussed above), would have to address and resolve difficulties in delivery time data collection as an initial step. The PAT would have to do a thorough review of what data are required at what level of detail in order to effectively measure the key variables of the delivery process. This includes, as a start, a stratification of the delivery time data collected so that the time replenishment orders spend in each stage of the order cycle can be collected, retrieved and analyzed. A PAT could also provide valuable insight and help assure the success of upcoming process improvement initiatives at OO-ALC such as the PACER INTEGRATE program, and the SC&D implementation. A PAT with members from all applicable work areas in MA and DS would ensure that these initiatives could improve material support to Depot Maintenance activities. The next section presents simulation experiment analysis on the effects that reduced mean and standard deviation values of in-transit delivery times have on inventory stockage performance.

Impact of Reduced Mean and Variance of In-Transit Delivery Time

The purpose of this final analysis was to analyze the effects that projected reductions in mean and standard deviation values of in-transit delivery time would have on simulated inventory performance in the MIC. This analysis focused on MIC MCC since this was the only MIC investigated where an adequate fit to a theoretical probability distribution was obtained for the in-transit delivery time data. Proposed reductions in empirical lead time mean and standard deviation values of 10, 20 and 50% were analyzed. In order to better understand the effects that reduced mean and standard deviation values of delivery lead time have on simulated inventory performance, a brief examination into how these reduced values effect the shape and appearance of the hypothesized beta distribution is discussed first. Then, simulated LIFR results for the MIC MCC for an item where $\lambda = 2$, and $\beta = 12$ are presented and analyzed using the hypothetical 10, 20, and 50% reductions of mean and standard deviation of in-transit delivery time as the main input parameters of interest.

Impact on Beta Distribution Parameters, Shape and Appearance. Reducing the mean and standard deviation measures of in-transit delivery time drastically changes the beta distribution's α and β parameters, as well as the shape of it's corresponding PDF curve. Applying the methodology described in Appendix K, alpha and beta parameters for a beta distribution were computed for various hypothetical levels of mean and standard deviation of in-transit delivery times. The minimum and maximum points of the distribution parameters computed were held constant at 1.11 and 7.767 days, respectively, as observed from the MIC MCC data set. It should be noted that by changing the original mean and standard deviation values, the underlying characteristics of a distribution can change drastically. The minimum and maximum points may shift to lower values as a result of reducing the mean and standard deviation. However, to simplify analysis of reduced mean and standard deviation effects on beta-distributed lead times, the minimum and maximum points were held constant.

Table 9 shows the corresponding α and β parameters for the beta distribution when the in-transit delivery time's mean and standard deviation are reduced by 10, 20, or 50% either exclusively or in combination.

Table 9. Alpha and Beta Parameters for MIC MCC

		Standard Deviation of Lead Time in Days (σ)			
Mean Lead Time in Days (μ)		1.848 (Actual)	1.663 (-10%)	1.478 (-20%)	0.924 (-50%)
3.626	α	0.7752	1.0459	1.4247	4.2342
(Actual)	β	1.2760	1.7214	2.3448	6.9689
3.263	α	0.5949	0.8106	1.1123	3.3499
(-10%)	β	1.2446	1.6958	2.3268	7.0080
2.901	α	0.4175	0.5788	0.8043	2.4772
(-20%)	β	1.1344	1.5725	2.1852	6.7304
1.813	α	0.0238	0.0542	0.0967	0.4121
(-50%)	β	0.2018	0.4593	0.8193	3.4904

For example, the new α and β parameters when the mean in-transit delivery time is reduced by 50% (1.813 days) and its standard deviation is reduced by 50% (0.924 days) is shown in the lower right corner of the table.

The above combinations of mean, standard deviation, alpha and beta parameters were input into the AID distribution-fitting program. Appendix L presents graphically how the beta distribution's PDF curve responds as the input parameters vary. Figure 16 shows the original hypothesized beta distribution fit to the original 5-month data sample for MIC MCC. In Figures 17-31, the hypothetical PDF curves resulting from mean and standard deviation reductions are portrayed by the broken lines superimposed over a histogram of the original 5-month data sample for MIC MCC.

In reviewing the diagrams displayed in Appendix L, it is quite evident that reductions in mean and standard deviation can dramatically impact the shape of the PDF curve. It is especially evident for reductions of 50%. For example, the original, or actual data PDF curve appears more normally or lognormally distributed as the standard deviation is reduced to 50% of the original value (Figures 17 to 19). As the mean is reduced to 50% of the original value, the resulting PDF curve becomes "U-shaped" (Figures 20, 24 and 28). With both the mean and standard deviation reduced to 50% of the original values, the PDF curve appears exponentially distributed (Figure 31). The change in shape of each of these PDF curves also suggests that randomly generated lead time values based on hypothetical reductions in the mean and standard deviation of lead time can be quite different than those generated from the original empirical distribution. Thus, when reductions in either the mean or standard deviation of lead time (or both) can be achieved, they may have profound impacts upon delivery system performance. In the next section, simulated inventory performance based on the various proposed reductions of in-transit delivery time mean and standard deviation values is analyzed.

Simulated Impact on Stockage Performance. The LIFR performance results of simulation experiments for MIC MCC with the proposed reductions in mean and standard deviation of lead time are presented in Table 10. Recall that the baseline simulated LIFR performance in MIC MCC for an item with $\beta = 12$, and $\lambda = 2$ for the actual lead time $\mu = 3.626$ days and $\sigma = 1.848$ days was 84.3%. This value is shown in the uppermost left cell of Table 10. This value and the other simulated values in Table 10 should be

Table 10. LIFR (%) Performance for MIC MCC for Reduced μ and σ Values

	Standard Deviation of Lead Time in Days(σ)			
Mean Lead Time in Days(μ)	1.848 (Actual)	1.663 (-10%)	1.478 (-20%)	0.924 (-50%)
3.626 (Actual)	84.3	84.3	84.2	82.3
3.263 (-10%)	84.0	85.4	86.0	84.5
2.901 (-20%)	89.6	87.0	89.6	86.0
1.813 (-50%)	94.1	95.0	94.4	92.5

compared to the 95% LIFR objective that has been established for MIC stockage performance.

Table 10 shows that as the mean is decreased from the original value by 10, 20 and 50%, a steady increase in LIFR results for all values of standard deviation (except once when $\mu = 3.263$ and $\sigma = 1.848$). The improved LIFR performance can be seen by examining each column of data from top to bottom. In most cases where a 50% reduction in the mean lead time was examined, the resulting LIFR increased an additional 10% over the original value of 84.3%. This implies that for MIC MCC, where delivery times are beta-distributed, much improved LIFR performance can result if efforts are made to reduce the mean in-transit delivery times. Though only one case actually satisfied the 95% LIFR objective, improved MIC support results by decreasing the mean of in-transit delivery times.

The impact that reductions in standard deviation have on LIFR performance is not as evident from reviewing Table 10. In fact, LIFR appears to decrease in many cases as the standard deviation values are decreased by 10, 20 and 50%. Recall the effects that reduced standard deviation values had on PDF curves displayed in Appendix L. Reducing the standard deviation by 50% produced PDF curves that sometimes appeared normally, lognormally, or even exponentially-distributed. As the variance is reduced, some deliveries occurring in the left-hand tail of the PDF are lost. This is unfortunate, since these unusually short delivery times result in more stock being available on the MIC's shelves. The net result for the simulation experiments displayed here is that reducing the mean delivery time has much greater impact than reducing the variance.

While reducing the standard deviation drastically affects the possible values of lead times drawn from the specified beta distribution, no firm conclusion can be drawn on the effects that reduced standard deviations have on LIFR. However, improved LIFR performance is likely to result over that observed for the original mean and standard deviation parameters when the mean lead time is reduced. This implies that reductions in mean lead time will allow the 15/7 day inventory policy to provide improved support when in-transit delivery times are beta-distributed.

Chapter Summary

Chapter IV has examined several areas. First, the existing standards for in-transit delivery times, and how they were developed, were examined. Recent initiatives within AFLC, either planned or in-progress, to improve inventory management by integrating, automating and simplifying the overall process were then discussed. Next, empirical measures of lead time mean and variance were presented. Appropriately-fitting theoretical distributions were then proposed to fit the lead time data. After that, the difference between the G402A-maintained in-transit data and off-line issue document in-transit lead times was examined. Next, simulation experiments were analyzed that derived estimated inventory performance measures for various demand and in-transit delivery time parameters. SPC and the principles of continuous process improvement and variance reduction were shown to be useful for identifying potential areas to reduce the mean in-transit delivery time of assets to achieve the desired 1.5 day delivery time goal. Finally, additional simulation experiments demonstrated that reduced mean delivery times results in improved inventory performance and material support for maintenance work centers.

The next chapter summarizes this research effort, and presents conclusions drawn from the findings and analysis. Next, methodological issues concerning the various research activities conducted are considered. Then, some suggested areas for follow-on research efforts are proposed. Finally, recommendations based on research analysis, findings, and conclusions are presented.

V. Conclusions and Recommendations

Research Summary

As noted in Chapter I, there has been strong emphasis from HQ AFLC to reduce stock levels in MICs at the ALCs. No more than 15 days worth of stock is authorized for stockage in the MICs for direct material, regardless of the ERRC (either XB3, XF3, or XD2) assigned to an item, and regardless of whether the item is an investment or expense asset. The reorder point was not specifically outlined in recent AFLC guidance, except that replenishment should occur when the on-hand stock is "half-gone or earlier, if experience indicates additional order and ship time is required" (8:49). This policy implies that the 15/7 day inventory policy studied throughout this thesis is affected by stock replenishment in-transit delivery times. Excessive or highly variable in-transit delivery times can result in degraded inventory support in light of recent reductions in authorized MIC stockage levels.

As a starting point, the existing in-transit delivery time standards established in AFM 67-1 were examined. The "12-working hour/1.5-working day" standard for delivery priority 6 MIC stock replenishment orders was not established as a result of an elaborate delivery system capability study at the ALCs. Rather, it was based on a heuristic judgement on what would be an adequate time frame for asset delivery from DS to MA. No formal study has been conducted on what the standards should be to provide adequate support to on-base customers. A study is under way at HQ AFLC to determine what in-transit delivery times are being experienced at the five ALCs. The HQ AFLC study, which includes all delivery priorities from 1 to 6, will attempt to determine what the current capability is, and what delivery time standards should exist. Also, it is interesting to note the issue documents sampled in the AFLC study were rarely annotated with the time and date of receipt by MA personnel, which makes it difficult at best to track in-transit delivery times on a reliable basis.

Several initiatives are planned or on-going within AFLC to address problems with excessive in-transit delivery times. The recent decrease in maximum stock levels authorized in the MICs (the 15/7 inventory policy) reflects partial adoption of the just-in-time philosophy and its associated emphasis upon prompt delivery times. Excessive inventory levels can hide operational inefficiencies (such as slow delivery times), and result in increased inventory carrying costs. Eliminating or reducing what might be unnecessary stockage of parts requires improved overall operating efficiency, including the timeliness of stock replenishment deliveries.

The PACER INTEGRATE initiative was briefly described in Chapter IV. The test program slated to start January 1990 at OO-ALC will provide valuable insight into whether realignment of inventory management responsibilities under DS will improve supply support to Depot Maintenance activities. Finally, automation of inventory processes is already a reality at the ALCs. Many automated and mechanized material storage and distribution systems are already in place at OO-ALC, and the other ALCs as well. One primary area of concern for the future is the successful implementation of the SC&D and DCR systems. These data systems will result in the automated means to track asset deliveries from order initiation until receipt. The use of bar code technology will automate a system that is currently unable to fully track all material in the delivery process.

Analysis and evaluation of the in-transit delivery time data collected for this study was presented in Chapter IV. First, empirical means and standard deviations of delivery lead times were presented. There was only one case where the 1.5 day delivery standard was achieved (based on the G402A-maintained clock hour/calendar day data). In general, MIC MCC displayed the highest overall mean and standard deviation measures of lead time, meaning that it ran the greatest risk of inadequate MIC stockage, and therefore potential work stoppages. The beta distribution provided an adequate fit to MCC lead time data. MICs MDD and MFF, on the other hand, could not be characterized adequately by any of the 10 theoretical distributions investigated. As noted in Chapter II, lead time data is sometimes so variable that it may not fit familiar theoretical probability distributions, or it may shift around in no discernable pattern. Given the lack of adequate statistical fit, lognormal distributions (which came closest to fitting the data), were used to characterize lead time for MICs MDD and MFF in simulation experiments.

Next, the difference between in-transit lead time data maintained on the G402A, and lead times derived from off-line issue documents was investigated. The time of receipt by MIC personnel was seldom annotated on the 171 documents included in the sample analyzed, similar to the experience noted in the HQ AFLC's delivery lead time study. The difference between the document clearance times and dates, and the G402A times and dates provides an estimate of the time required to clear the transaction from the G402A system after physically receiving the material. The nonparametric Wilcoxon Signed-Rank test supported the hypothesis that the average difference of 0.744 days between the two measures of lead time was significantly significant. This value was used to correct O&ST values based on G402A parameters generated in subsequent simulation experiments. Also, if 0.744 days was subtracted from the empirical mean lead times, 13 of the 36 samples (or approximately 36%) would satisfy the 1.5 day delivery standard, with the remaining 64% of the samples still exceeding the standard.

A more reliable measurement of the time lag between the receipt of the asset by the MIC and the actual addition to stock (that is, processing the clearance transaction through the G402A) is suggested for follow-on research. Under the SC&D and DCR systems, perhaps a reliable, automated and usable database will be available. The in-transit delivery time should be recorded so that the duration of the major segments of the order cycle time are known, allowing the true problem areas to be detected. Automated systems such as SC&D and DCR, using state-of-the-art bar code and data processing technology are a necessity for more effective control and continuous improvement of the delivery process.

Simulation of the impact that in-transit delivery time has on inventory performance measures was then presented in Chapter IV. These simulations were conducted based on varying levels of Units per Request (λ), Days between Requests (β), and O&ST mean, standard deviation and hypothesized probability distributions. In general, it was found that more frequently demanded items achieved the highest LIFR and UFR values. As the frequency of demand decreased, LIFR and UFR performance degraded as well, and the average on-hand inventory also decreased.

Backorder-days and backordered units were significantly higher for mid-range frequency of demand items, especially for MICs MDD and MFF.

McBride found that these two MICs experienced significantly higher units per request. The 15/7 inventory policy combined with the empirical O&ST parameters were less capable of providing adequate support for those MICs. The 15/7 day inventory policy and the empirical O&ST parameters were the prime contributors to degraded inventory performance measures, especially for the medium and low frequency of demand items which had relatively high units demanded per request.

The applicability of quality control concepts and tools was explored next. Opportunities for reduction of mean and standard deviation measures of in-transit delivery time were presented using control charts. The control charts indicated where assignable causes of variation might have occurred. The data displayed a large amount of variation in the delivery process, presumedly due to assignable causes that, under the scrutiny of a PAT, could conceivably be applied to improving the overall process capability. In spite of the significant variation and instability in the delivery process indicated by the control charts, the quality control principles discussed seem applicable to regain "control" over the process. Furthermore, the principles of QP4, variance reduction, and the formation of a PAT seem a viable means to improve the process so that the desired 1.5 day in-transit delivery times are obtained.

The biggest hurdle preventing effective confrontation and resolution of excessive delivery times is the lack of prompt, reliable data measuring the process in sufficient detail to be useful. The data collected for this study was available only after a significant amount of manual effort, and measured observed lead time data that was weeks or months-old when earnest analysis was finally accomplished. Control and improvement of a process cannot occur if the necessary data is days, weeks, or even months old. Additionally, the data were not originally aggregated or stratified at the level of detail necessary to detect the "logjams and bottlenecks" in the delivery process.

Again, the focused study of a PAT could yield precise definitions of the data required to study and analyze the process. The data requirements could then be included and made available through upcoming automated data systems such as the SC&D and DCR process. Additionally, a PAT formed at OO-ALC could be the key to the successful test of the PACER INTEGRATE program. In short, the formation of a PAT to study the delivery process may be the only way to provide systematic improvement of the process, and maximize delivery process capability and performance.

Finally, the impact of proposed reductions of mean and standard deviation measures of in-transit delivery time was examined. Proposed reductions of 10, 20 and 50% in lead time mean and standard deviation measures were evaluated in simulation experiments for MIC MCC using 12 days between requests and 2 units per request as input parameters. Reducing the mean and standard deviation values of lead time causes drastic changes to occur in the shape and appearance of the beta probability density function curve. Reductions in mean lead time values resulted in steady increases in LIFR performance, indicating that the 15/7 inventory policy can provide improved support if mean delivery time is reduced. However, decreasing the standard deviation of lead time caused small, but unpredictable increases and decreases in LIFR. This was attributed to the drastic change in the shape and appearance of the beta probability density function for extreme reductions in the standard deviation of lead times.

Because of this, analysis of the beta-distributed lead times simulated in this study suggest that the focus of any future studies should be on reducing the mean in-transit delivery time for MIC MCC. One caution, however, is appropriate: Changes to delivery systems supporting MIC MCC may also change the underlying delivery time distribution. Thus, a cycle of change and analysis must be continuously performed.

Research Conclusions

The in-transit delivery time data collected and analyzed for this study have shown that the existing delivery standards for MIC replenishment issues are not being met. Additionally, simulation results imply that the 95% LIFR objective is achieved only for a limited number of items characterized by a high frequency of demand (low number of days between requests). The in-transit delivery time mean, variance, and probability distribution, coupled with the 15/7 day inventory policy for replenishment of stock in the MICs were found to be strong factors influencing inventory performance measures. In general, reducing the mean of in-transit delivery time results in improved material availability in the MICs for the case of beta-distributed lead times.

Additionally, the labor-intensive data collection and analysis effort required to measure the delivery process with currently available data systems was a substantial obstacle to timely, effective and proactive measurement and control over the delivery process. Before improvement of the process can be realized, automated data systems such as the SC&D and DCR process systems must be implemented. Further, the necessary data must be available to provide reliable and timely measurement of an asset's progress through the order cycle, from the receipt of the order in DS, to the actual addition into stock in the MA work areas.

Methodology Issues

The in-transit delivery time values presented throughout this study represent continuous clock hours and calendar days. Holidays, weekends and other production down times (some MICs operate 24 hours a day, while others operate only one or two shifts per day) were not distinguishable in the G402A database. That is, the time between notification of delivery and the actual receipt and clearance of the transaction is measured on a continuous clock hour versus working hour, and calendar day versus working day basis.

Additionally, in order to determine if a significant difference existed in hard copy, documented versus computerized G402A lead times, some assumptions were necessary due to the nonavailability of signature times and dates on the off-line issue documents. Those documents that had the same clearance date as the G402A-date were considered "on-time." That is, the difference between the two transactions was zero, indicating no statistically significant difference between the two transactions. Documents that had clearance dates (but no signature times) before the G402A date for the same transaction were considered cleared at 1600 hours of that day. The off-line delivery time value was computed from this time and date. The delivery time difference between the off-line value and the value computed from the G402A data signifies the time lag involved after receipt until actual clearance in the G402A data system. This method provided a general estimate for input into the simulation experiments. A more reliable means of collecting this data, such as with an automated system using bar code technology would allow for better aggregation of lead time data into the order cycle time/lead time segments defined by Tersine, and Stock and Lambert in Chapter II.

Since McBride's simulation model was used for a large portion of this study, similar assumptions noted in his study apply to this effort as well:

> The MIC simulations made an assumption that D033 always had enough stock on hand to fill a MIC replenishment request. This method of simulating MIC replenishments may overstate the ability of D033. The result is that the simulated fill rates [and other performance measures as well] may be more appropriately considered upper limits. It is also noted that the results of the simulations suppose perfect knowledge of the demand distributions and [in-transit] times. Although actual responses would not be expected to occur exactly according to some theoretical distribution, the results provide a sound basis for relative comparison. (22:73)

Related to this cautionary note is a reminder that simulation experiments presented for MICs MDD and MFF used lognormal distributions in spite of a lack of statistically significant evidence of "goodness-of-fit." The results of these experiments should be considered with this in mind. Additionally, the proposed reductions in mean and standard deviations of lead time for MIC MCC experiments were based on the assumption that the minimum and maximum values would remain constant. The effects that reduced mean and variance values have on corresponding minimum and maximum values generated from a beta distribution is recommended as a follow-on research effort.

Suggestions for Follow-on Research

Additional research is required to determine exactly what types of descriptive data should be incorporated into the SC&D/DCR database to allow earnest analysis of the delivery process. The procedure used in this study is too labor intensive and not time-sensitive enough to provide adequate data on a reliable, usable and timely basis. For any effective analysis of the delivery process at OO-ALC and the other ALCs to be fruitful, a more effective means must be made available to provide the necessary data and analysis capability. A survey or series of interviews with workers, managers and analysts at the ALCs and HQ AFLC into what data would be useful to maintain on the SC&D and DCR systems is suggested. A thorough review of the hardware and software system design and planning documents would yield information on what is programmed for inclusion into the systems upon implementation. Recommendations based on findings from surveys and interviews with concerned workers, managers and supervisors could help designers and end users prevent shortfalls in the SC&D/DCR system architecture.

With the IOC of SC&D planned for December 1989, and the testing of the PACER INTEGRATE planned to start in January 1990, a case study into the implementation of these two projects is a worthy opportunity for related follow-up research. Objective evaluation of these two initiatives would serve to ease the burdens of implementation efforts at the other ALCs. Additionally, more focused study into the application of the QP4, PAT and continuous process improvement concepts to address shortfalls in the current process capability would be invaluable.

In spite of the difficulty and large amount of manual intervention required to collect and analyze the necessary data, analysis to include the other ALCs would be fruitful. The time frame for analysis might be expanded to more than the six months of sample data analyzed in this effort. Follow-up study to the HQ AFLC delivery lead time study scheduled for completion in September 1989 may perhaps result in an adequate database for additional study. Evaluation of the delivery process capability for all delivery priorities and other base customers might be possible with data compiled and analyzed in the HQ AFLC study. Finally, analysis into the order and ship times experienced for the delivery of assets from off-base sources of supply is another area for research opportunity.

Recommendations

This study has shown that mean and variance measures of in-transit delivery time has a significant impact on simulated inventory performance measures. By reducing the mean and variance of delivery lead times, improved material availability in the MIC forward stockage points is likely to result. However, several areas require additional attention before the delivery process can be improved by reducing lead time mean and variance measures. First, the lack of reliable and usable lead time data is a large obstacle. A review of the necessary data elements required in upcoming data systems such as the SC&D and DCR process is essential to ensure these automated systems can provide access to needed in-transit delivery time data. A PAT composed of key workers, technicians and managers from all work areas involved with the delivery process should be assembled to study and continuously improve the process, with a review of the required data and measurement systems being the first step.

Second, after completion of the AFLC delivery time study (scheduled for September 1989), a review of the existing delivery standards is necessary. Since this study will be the first effort to assess delivery lead time capability, it may be found that the existing standards are too stringent to be met by the current process capability. Thus, either on-base delivery capabilities must be improved or alternative inventory policies implemented.

Third, after test and evaluation of the PACER INTEGRATE program at OO-ALC, it may be found that the forward stockage points operated by DS personnel provide adequate material support to the MA work areas as envisioned by the current program goals and objectives. Under the PACER INTEGRATE operational concept where DS is required to provide decentralized material support to MA work areas, emphasis will probably shift from evaluating DS delivery performance to more direct measures of inventory support, such as LIFR, UFR, or other key indicators of material support. Nonetheless, timely material delivery between DS and MA will still play an important role in supporting Depot Maintenance activities.

Appendix A: Sample of Local Issue Document

OC48 REC # 0624 RECEIVED: 334.12:40:21

LOCAL ISSUE DOCUMENT

DOC ID	ROUT ID	T T	STOCK NUMBER	UNIT ISSUE	QUANTITY	DOCUMENT NUMBER	SUFX	SHIP TO	CUSTOMER FUNCT CODE	PROJ CODE	URG F/A	INSP CODE	ADV CODE	PRI	SHELF LIFE
D7A	MCC	M	5360004356548TP	EA	00004	MBPABA83272175					C 3	XXX		6	0

OP	COND	MGMT	CUSTODY ACCT	COST	WAREHOUSE LOCATION/LINE NUM	SEC	COND	SUBSTITUTE DATA (ORIGINAL REQUEST ITEM)	INV CD	DIFM	MGR DSG	RE-IMB	FUND CODE	MI CAP	ERRC	CRIT
A	A	M				U	A	FB2029B3260582			HK	3	6H		NA	

MGR REV	PROCESS DATE	DELIVERY TIME	ISSUE FROM	TOTAL PRICE DOLLARS.CTS	XREF/REV XREF STOCK NUMB -OR-DATE OF LAST RECEIPT	SELECTED BY	DATE/TIME	JON
	8334	3360743		0000001352	88334			1243

PACKED BY	# CTNS	DATE/TIME	RECEIVED BY	DATE/TIME	BINNED BY	DATE/TIME

MBPABA83272175

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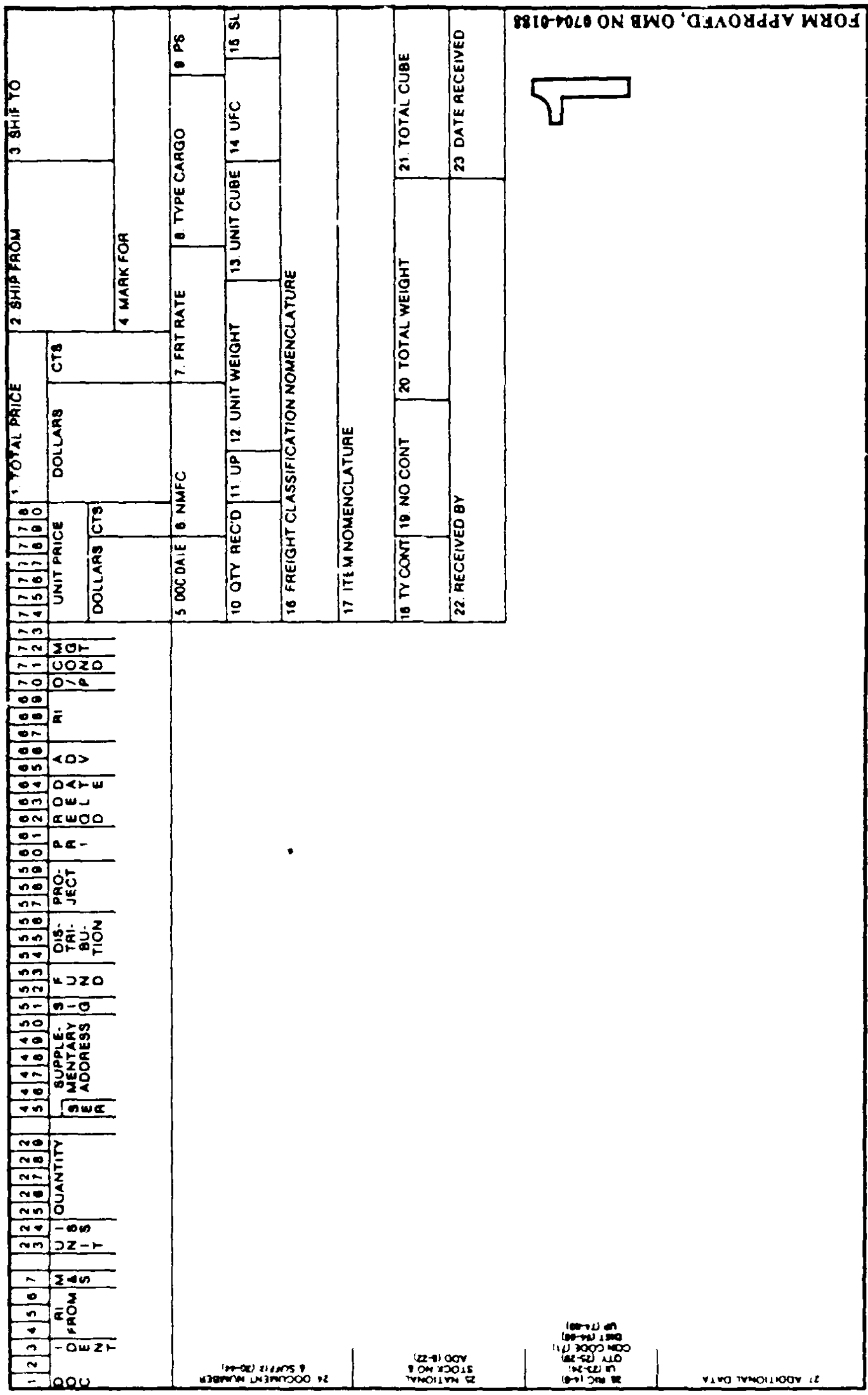
Appendix B: Sample of DD Form 1348-1A



FORM APPROVED, OMB NO 0704-0188

1 TOTAL PRICE
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UNIT PRICE
DOLLARS
CTS
2 SHIP FROM
3 SHIP TO
4 MARK FOR
5 DOC DATE
6 NMFC
7. FRT RATE
8 TYPE CARGO
9 PS
10 QTY REC'D
11 UP
12 UNIT WEIGHT
13. UNIT CUBE
14 UFC
15 SL
16 FREIGHT CLASSIFICATION NOMENCLATURE
17 ITEM NOMENCLATURE
18 TY CONT
19 NO CONT
20 TOTAL WEIGHT
21. TOTAL CUBE
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23 DATE RECEIVED
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UNIT ISSUE
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SER
SUPPLEMENTARY ADDRESS
SIG
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COND
MGT
24 DOCUMENT NUMBER & SUFFIX (30-44)
25 NATIONAL STOCK NO & ADD (8-22)
26 RIC (4-6) UI (23-24) QTY (25-29) CON CODE (71) DIST (64-66) UP (74-80)
27 ADDITIONAL DATA
PREVIOUS EDITION MAY BE USED UNTIL EXHAUSTED

DD FORM 1348-1A, NOV 87 ISSUE RELEASE/RECEIPT DOCUMENT

Appendix C: Sample of DS-MIC In-Transit Data (Reprinted from 22:87)

DOC ID	MIC	NSN	UI	QTY	DOC NR	AC SF	T R	DATE	TIME
INT	MSS	5330012485451AQ	EA	67	MKMMSS70743104		R	88170	172347
INT	MSS	5330012485451AQ	EA	67		CL	I	88173	080541
INT	MSS	1420011112149GF	EA	1	MKMMSS72241847	CL	I	88154	073805
INT	MSS	5905001391375JB	EA	3	MKMMSS72252576		R	88162	171711
INT	MSS	5905001391375JB	EA	3		CL	I	88176	122712
INT	MSS	4710002287643BF	EA	3	MKMMSS80491739	CL	I	88153	130507
INT	MSS	5962012521486	EA	1	MKMMSS80684170		R	88172	190907
INT	MSS	5962012521486	EA	1		CL	I	88173	142357
INT	MSS	1430003980384BF	EA	2	MKMMSS81042380		R	88165	192651
INT	MSS	1430003980384BF	EA	2		CL	I	88169	124710
INT	MSS	5995001309164BF	EA	1	MKMMSS81312544		R	88167	225859
INT	MSS	5995001309164BF	EA	1			O	88168	101723
INT	MSS	5961001051987	EA	9	MKMMSS81332566		R	88169	131806
INT	MSS	5961001051987	EA	9		CL	I	88172	142410
INT	MSS	6670011784749	EA	3			R	88155	214955
INT	MSS	6670011784749	EA	3		CL	I	88159	105718
INT	MSS	6670011784743	EA	8	MKMMSS81402092	CL	I	88153	130444
INT	MSS	1420001853505CJ	EA	1	MKMMSS81451233	CL	I	88154	073340
INT	MSS	1420003500959CJ	EA	1	MKMMSS81451239		R	88166	104033
INT	MSS	1420003500959CJ	EA	1		CL	I	88169	124437
INT	MSS	5962011784364	EA	5	MKMMSS81471099		R	88153	090815
INT	MSS	5962011784364	EA	5		CL	I	88154	081255
INT	MSS	5962011237453	EA	5	MKMMSS81471514	CL	I	88154	073530
INT	MSS	1430003293133BF	EA	6	MKMMSS81471515	CL	I	88154	073442
INT	MSS	5961007643161	EA	4	MKMMSS81471521	CL	I	88154	073356
INT	MSS	5990000558429	EA	10	MKMMSS81471526	CL	I	88154	073715
INT	MSS	5905000588616	EA	3	MKMMSS81471528	CL	I	88154	073747
INT	MSS	5962001470790	EA	4	MKMMSS81471672	CL	I	88154	073615
INT	MSS	5945001538761	EA	3	MKMMSS81472053	CL	I	88154	073600
INT	MSS	1430009972074BF	EA	3	MKMMSS81472056	CL	I	88154	073514
INT	MSS	1430000170561BF	EA	2	MKMMSS81472058	CL	I	88154	073732
INT	MSS	1430002457948BF	EA	3	MKMMSS81472060	CL	I	88154	073306
INT	MSS	5961008254623BF	EA	2	MKMMSS81472085	CL	I	88154	073645
INT	MSS	5935000522668	EA	10	MKMMSS81481470	CL	I	88154	073212
INT	MSS	5935000522667	EA	6	MKMMSS81481472		R	88158	232439
INT	MSS	5935000522667	EA	6		CL	I	88162	100733
INT	MSS	5935000502152	EA	4	MKMMSS81481473	CL	I	88154	073411

Appendix D: TANDEM ENFORM Interrogation Routine to Extract In-Transit Data from ADS G402A (Reprinted from 22:88)

```
?DICTIONARY  $DATA.QRADDL
?ASSIGN QRM1COTH,$DATA15.QRADBA.QRM1COTH,SHARED
?OUT \LAB.$S.#WANE
OPEN QRM1COTH;
LIST
        DOC-ID                    OF QRM1COTH  HEADING "DOC/ID",
        MIC                       OF QRM1COTH  HEADING "MIC",
        TYP-TRANS-CD              OF QRM1COTH  HEADING "T/T",
        STKNBR                    OF QRM1COTH  HEADING "NSN",
        UNIT-OF-ISS               OF QRM1COTH  HEADING "UI",
        QTY                       OF QRM1COTH  HEADING "QTY",
BY      DOC-NBR                   OF QRM1COTH  HEADING "DOC NR",
        DEMAND-SFX                OF QRM1COTH  HEADING "D/S",
        INT-BIN-LOC               OF QRM1COTH  HEADING "IBL",
        PRI-CD                    OF QRM1COTH  HEADING "PRI",
        JON-SFX                   OF QRM1COTH  HEADING "JON/SFX",
        ADV-CD                    OF QRM1COTH  HEADING "ADV/CD",
        ACT-SFX                   OF QRM1COTH  HEADING "AC/SF",
        TYP-TRAN-HIST-CD          OF QRM1COTH  HEADING "T/R",
        PROC-DATE-2               OF QRM1COTH  HEADING "PDATE",
        PROC-TIME-2               OF QRM1COTH  HEADING "PTIME",
WHERE (MIC OF QRM1COTH = "MFF") AND (DOC-ID OF QRM1COTH = "INT")
AND (PROC-DATE-2 = "88153" THRU "88182");
CLOSE QRM1COTH;
```

Appendix E: Sample of D033 "TVA" Report (Reprinted from 22:77)

CA MTPFEM DEPOT MAINTENANCE MATERIAL SUPPORT AS OF 85151 OCALC A-D033.-TVA-TT-GTV PAGE 77

	DEMAND ACCOMMODATION AND OBJECTIVES				DEMAND SATISFACTION AND % TOTAL FILL OBJECTIVES							LESS THAN 100% SUPPORT	
	NUMBER DEMANDS	NUMBER MATCHED	% MATCH	% MATCH OBJ	NUMBER TOTAL FILL	% TOTAL FILL	% TOTAL FILL OBJ	# PARTIAL FILL	% PARTIAL FILL	# ZERO FILL	% ZERO FILL	# LESS 100%	% LESS 100%
					DIRECT MATERIAL SUPPORT								
MIC	205	171	83.4%	85%	132	77.1%	95%	25	14.6%	14	8.1%	73	35.8%
OS	74	41	55.4%	85%	41	100.0%	95%					33	44.5%
TOTAL	208	179	85.8%	85%	173	96.6%	95%					33	16.0%
FILLED FROM EXCESS					32							(32)	
FILL RATE	206				205	99.5%						1	
					INDIRECT MATERIAL SUPPORT								
U6100 BENCH STOCK	2	1	50.0%	85%			95%			1	100.0%	2	100.0%
FILL RATE	2											2	100.0%

Appendix F. Sample Sizes for Empirical In-Transit Delivery Time Data

	Month					
	December	January	February	March	April	May
MIC Identifier						
MCC	250	251	242	246	225	210
MDD	251	250	245	232	246	247
MFF	250	248	242	248	248	242
MBB	240	250	242	240	246	242
MHH	33 *	47 *	42 *	104 *	87 *	73*
MLL	182 *	190 *	229 *	193 *	212	234

(Note: Samples marked with an asterisk denote that they were 100 percent census samples of all MIC replenishment transactions for a given MIC during a given month).

Appendix G: Kolmogorov-Smirnov Goodness-of-Fit Test Results

	MIC Identifier		
	MCC	MDD	MFF
Required KS Test Statistic	0.0444	0.0435	0.0434
Theoretical Distribution			
Lognormal	0.0850	0.1060	0.1350
Exponential	0.2644	0.2780	0.2890
Erlang	0.0990	0.2040	0.2390
Gamma	0.0730	0.1500	0.1480
Weibull	0.0690	0.1570	0.1610
Beta	0.0370	0.1530	0.1720
Beta-PERT	0.2101	0.2710	0.2270
Uniform	0.1956	0.2876	0.2876
Triangular	0.1268	0.1762	0.1818
Normal	0.1020	0.2139	0.2307

Appendix H: MIC MDD and MFF Secondary Kolmogorov-Smirnov Test Results

Table 11. MIC MDD Secondary Kolmogorov-Smirnov Test Results

Test Number	Test parameters	Computed KS Test Statistic
1	μ = 1.800 σ = 1.307	0.1108
2	μ = 1.800 σ = 1.200	0.1410
3	μ = 1.800 σ = 1.400	0.1179
4	μ = 1.600 σ = 1.307	0.1896
5	μ = 1.600 σ = 1.200	0.1609
6	μ = 1.600 σ = 1.400	0.2126

Table 12. MIC MFP Secondary Kolmogorov-Smirnov Test Results

Test Number	Test parameters	Computed KS Test Statistic
1	$\mu = 1.5000$ $\sigma = 1.0880$	0.1602
2	$\mu = 1.5000$ $\sigma = 0.8834$	0.2181
3	$\mu = 1.5000$ $\sigma = 1.2000$	0.1365
4	$\mu = 1.2000$ $\sigma = 1.0880$	0.2690
5	$\mu = 1.2000$ $\sigma = 0.8834$	0.2048
6	$\mu = 1.2000$ $\sigma = 1.2000$	0.2974

Appendix I: Frequency Distribution Table for Observed Difference Data

Bar:	From: (≥)	To: (<)	Count:	Percent:
1	0.0	0.5	119	69.591
2	0.5	1.0	22	12.865
3	1.0	1.5	6	3.509
4	1.5	2.0	4	2.339
5	2.0	2.5	0	0.000
6	2.5	3.0	6	3.509
7	3.0	3.5	1	0.585
8	3.5	4.0	4	2.399
9	4.0	4.5	0	0.000
10	4.5	5.0	4	2.399
11	5.0	5.5	1	0.585
12	5.5	6 0	0	0.000
13	6.0	6.5	0	0.000
14	6.5	7.0	2	1.170
15	7.0	7.5	0	0.000
16	7.5	8.0	0	0.000
17	8.0	8.5	0	0.000
18	8.5	9.0	0	0.000
19	9.0	9.5	0	0.000
20	9.5	10.0	0	0.000
21	10.0	10.5	0	0.000
22	10.5	11.0	0	0.000
23	11.0	11.5	0	0.000
24	11.5	12.0	0	0.000
25	12.0	12.5	0	0.000
26	12.5	13.0	2	1.170

Appendix J: Sample Data Points for MIC MCC Control Charts

SAMPLE NUMBER	1	2	3	4	5	6	7	8
	0.877	2.198	2.090	2.639	1.427	0.881	1.637	1.630
	3.352	3.059	3.222	2.642	5.546	1.144	1.640	1.633
	3.427	3.111	6.896	2.642	5.815	2.512	1.677	1.636
	4.020	3.341	8.176	6.053	5.851	2.527	2.435	1.667
	4.030	3.508	8.181	7.593	6.145	3.196	2.436	1.668
	4.268	4.418	8.185	7.594	6.167	3.230	2.449	1.676
	4.349	6.089	8.186	7.596	6.668	5.137	3.155	1.677
	6.859	6.216	8.188	7.611	6.700	5.554	9.511	1.679
	6.859	8.385	8.192	7.615	13.874	5.801	9.512	1.687
	8.810	8.437	20.077	8.992	17.728	5.803	9.514	2.452
	14.944	8.530	20.093	15.385	18.350	13.326	9.909	9.461
$\bar{X}$	5.618	5.208	9.226	6.943	8.570	4.465	4.898	2.442
RANGE	14.067	6.332	18.003	12.746	16.923	12.445	8.272	7.831
NUMBER DEFECTIVE	10	11	11	11	10	9	11	11
PERCENT DEFECTIVE	90.909	100.000	100.000	100 000	90.909	81.818	100.000	100.000

$\bar{\bar{X}} = 4.779$ $\bar{R} = 8.299$ TOTAL DEFECTIVE = 220

SAMPLE NUMBER	9	10	11	12	13	14	15	16
	1.626	1.653	1.526	0.016	1.037	3.951	1.802	1.793
	1.626	1.655	3.100	1.622	1.037	4.551	2.845	2.844
	2.447	1.676	3.101	1.651	1.087	4.762	2.860	2.858
	3.095	1.682	3.108	1.672	1.170	4.774	3.458	2.859
	3.098	3.090	7.308	1.673	1.173	4.774	3.857	2.860
	3.099	3.102	7.310	1.683	5.610	6.110	3.874	2.860
	7.240	3.132	9.499	1.720	6.762	7.424	4.526	3.881
	7.316	7.312	9.502	3.092	7.236	7.433	4.549	3.882
	9.462	7.312	9.503	7.041	7.433	7.434	5.559	3.892
	9.504	9.500	9.503	9.499	7.757	8.790	5.569	3.900
	9.510	9.508	9.504	13.604	8.925	9.464	5.578	3.917
$\overline{X}$	5.275	4.511	6.642	3.934	4.476	6.315	4.043	3.231
RANGE	7.884	7.855	7.878	13.588	7.888	5.513	3.776	2.124
NUMBER DEFECTIVE	11	11	11	10	6	11	11	11
PERCENT DEFECTIVE	100.000	100.000	100.000	90.909	54.545	100.000	100.000	100.000

SAMPLE NUMBER	17	18	19	20	21	22
	1.701	1.810	1.800	0.951	0.049	0.948
	2.849	2.859	2.858	1.064	0.054	0.999
	2.870	2.862	2.860	2.846	0.715	1.234
	2.872	2.870	2.866	2.847	0.861	1.234
	3.880	3.852	3.851	3.842	2.897	1.238
	3.882	3.881	3.864	3.874	3.105	1.238
	3.892	3.893	3.867	3.876	4.308	2.842
	3.892	3.894	3.907	3.878	4.309	2.843
	3.893	3.895	3.908	3.879	4.309	2.935
	3.895	3.911	3.908	3.898	4.347	3.644
	6.893	6.892	3.912	3.899	4.829	10.288
$\overline{X}$	3.684	3.693	3.418	3.169	2.708	2.677
RANGE	5.192	5.082	2.112	2.948	4.780	9.340
NUMBER DEFECTIVE	11	11	11	9	7	5
PERCENT DEFECTIVE	100.000	100.000	100.000	81.818	63.636	45.455

Appendix K: Methodology Used to Derive Beta Distribution Parameters

The following equations are used in the SLAM II simulation language to obtain a random number in the range 0 to 1 that is drawn from a beta distribution:

$$\mu = (\mu_\beta - \text{MIN}) / (\text{MAX-MIN}) \qquad (14)$$

$$\sigma^2 = \sigma_\beta^2 / (\text{MAX-MIN})^2 \qquad (15)$$

where

μ_β = original mean value from the sample data

σ_β^2 = original variance from the sample data

MIN = Specified minimum value included in the distribution

MAX = Specified maximum value included in the distribution (28: 110, 715; 30)

With this transformation of the sample mean and variance, the arguments used by SLAM to generate a beta-distributed random number between 0 and 1 are:

$$\text{THETA} = (\mu^2 / \sigma^2)(1 - \mu) - \mu \qquad (16)$$

$$\text{PHI} = \text{THETA}((1 - \mu) / (\mu)) \qquad (17)$$

where

THETA = Alpha parameter for beta distribution

PHI = Beta parameter for beta distribution

μ = Transformed mean value computed in Eq (14)

σ^2 = Transformed variance value computed in Eq (15) (28:110, 715; 30)

Finally, in order to obtain a beta-distributed random number to represent the O&ST that is within the range of the MIN and MAX points defined above, the following equation was used in the simulation programs:

$$O\&ST = (BETA\ (\ THETA,\ PHI)\ )\ (\ MAX - MIN\ ) + MIN \qquad (18)$$

where

(BETA (THETA, PHI))	=	SLAM II function to generate a Beta-distributed random number with the specified THETA and PHI parameters
THETA	=	α parameter for beta distribution
PHI	=	β parameter for beta distribution
MIN	=	Specified minimum value included in the distribution
MAX	=	Specified maximum value included in the distribution (28:110, 715; 30)

Appendix L: Beta Distribution Curves with Various μ and σ Parameters

The following figures are included in this Appendix:

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940			

CELL WIDTH = 0.6657

SAMPLE STATISTICS:

MEAN = 3.626
STANDARD DEVIATION = 1.848
MINIMUM VALUE = 1.100
MAXIMUM VALUE = 1.767

HYPOTHESIZED DISTRIBUTION: BETA

PARAMETERS:

MEAN = 3.626
STANDARD DEVIATION = 1.848
MINIMUM VALUE = 1.110
MAXIMUM VALUE = 7.767
ALPHA = 0.7752
BETA = 1.2760

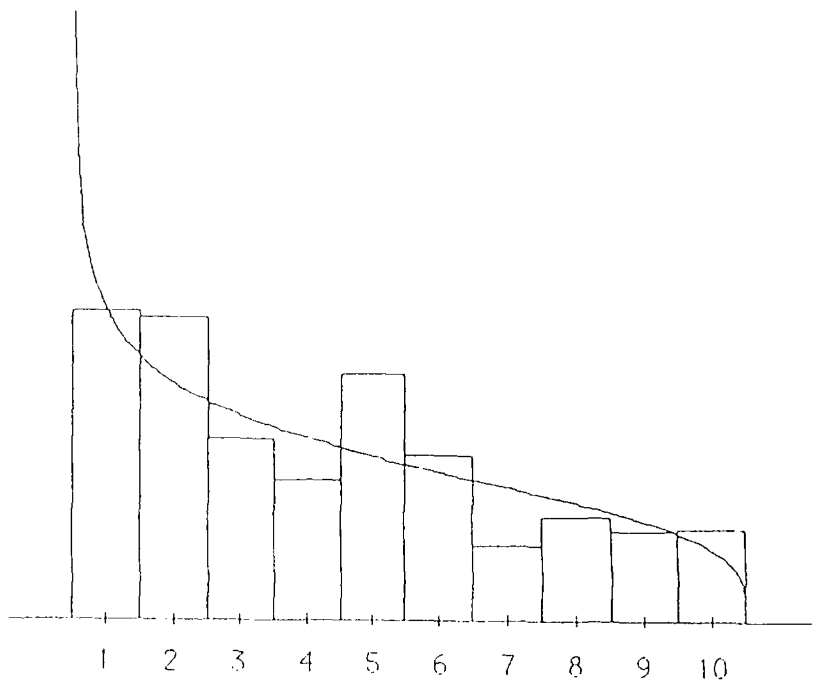

Figure 16. Beta PDF with Hypothesized μ and σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940			

CELL WIDTH = 0.6657

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN	= 3.626
STANDARD DEVIATION	= 1.663
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 1.046
BETA	= 1.721

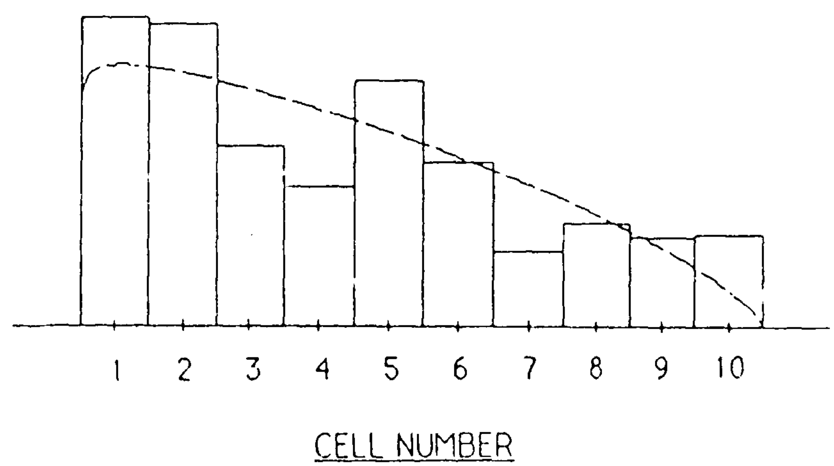

Figure 17. Beta PDF with 0% Reduced μ, 10% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940			

CELL WIDTH = 0.6657

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN	= 3.626
STANDARD DEVIATION	= 1.478
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 1.425
BETA	= 2.345

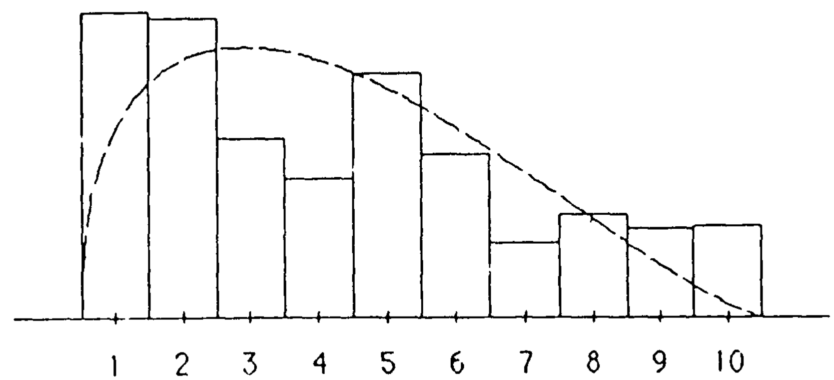

Figure 18. Beta PDF with 0% Reduced μ, 20% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN	= 3.626
STANDARD DEVIATION	= 0.924
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 4.234
BETA	= 6.969

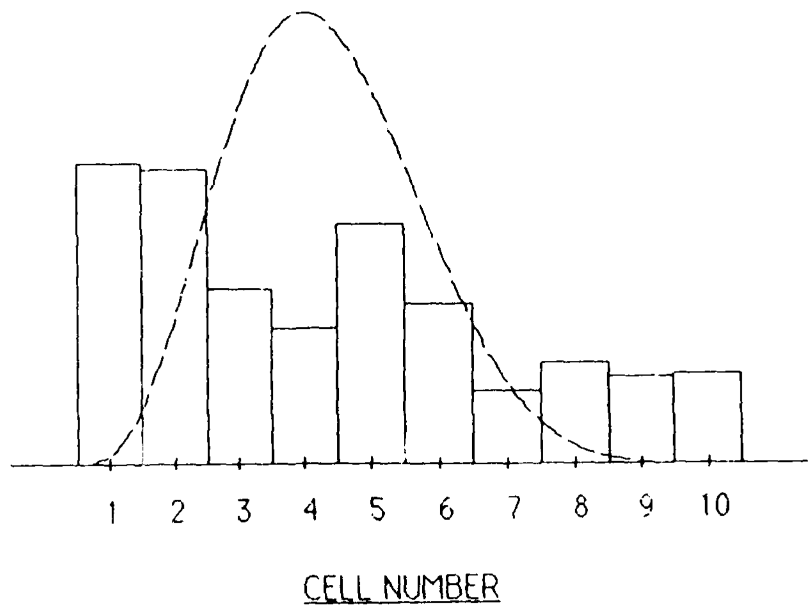

Figure 19. Beta PDF with 0% Reduced μ, 50% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN = 3.263
STANDARD DEVIATION = 1.848
MINIMUM VALUE = 1.110
MAXIMUM VALUE = 7.767
ALPHA = 0.5949
BETA = 1.2450

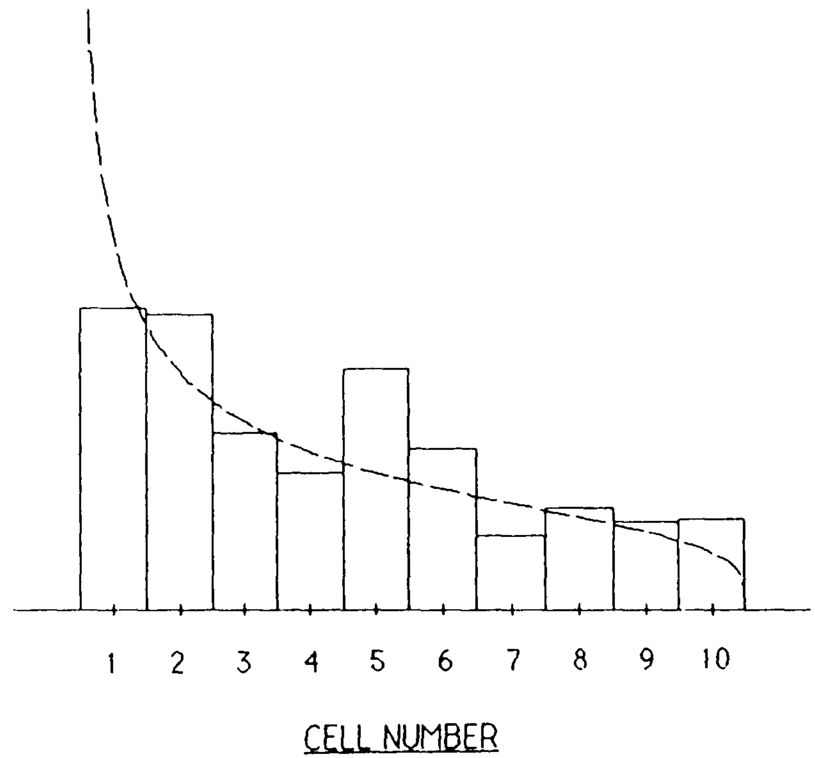

Figure 20. Beta PDF with 10% Reduced μ, 0% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN	= 3.263
STANDARD DEVIATION	= 1.663
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 0.8106
BETA	= 1.6960

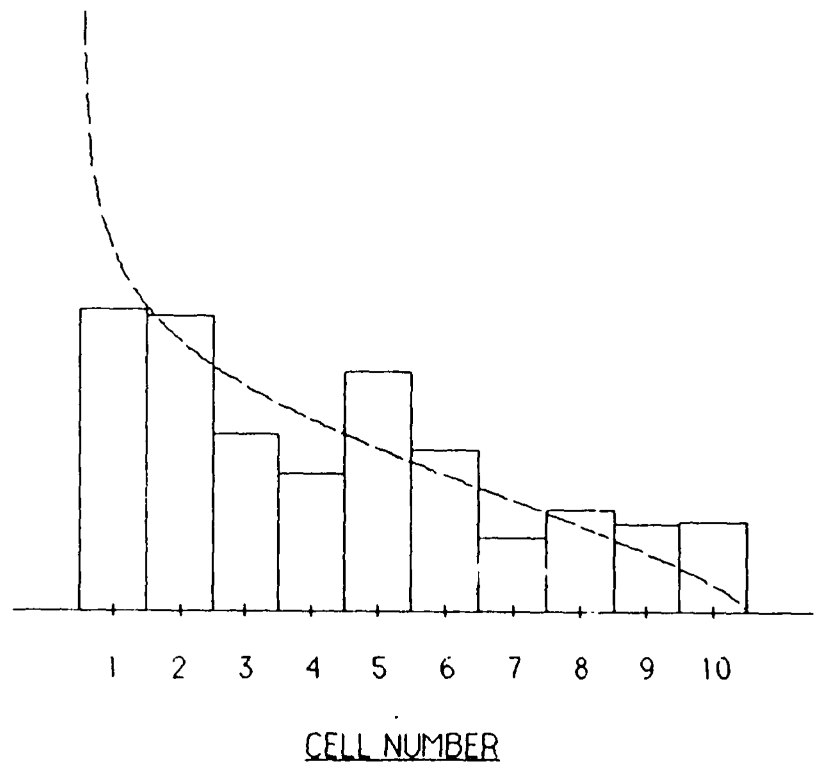

Figure 21. Beta PDF with 10% Reduced μ, 10% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN = 3.263
STANDARD DEVIATION = 1.478
MINIMUM VALUE = 1.110
MAXIMUM VALUE = 7.767
ALPHA = 1.112
BETA = 2.327

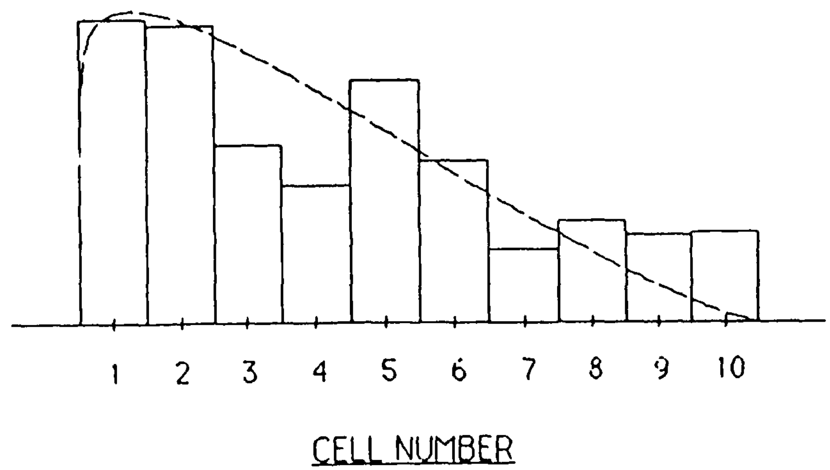

Figure 22. Beta PDF with 10% Reduced μ, 20% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940			

CELL WIDTH = 0.6657

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN	= 3.263
STANDARD DEVIATION	= 0.924
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 3.350
BETA	= 7.008

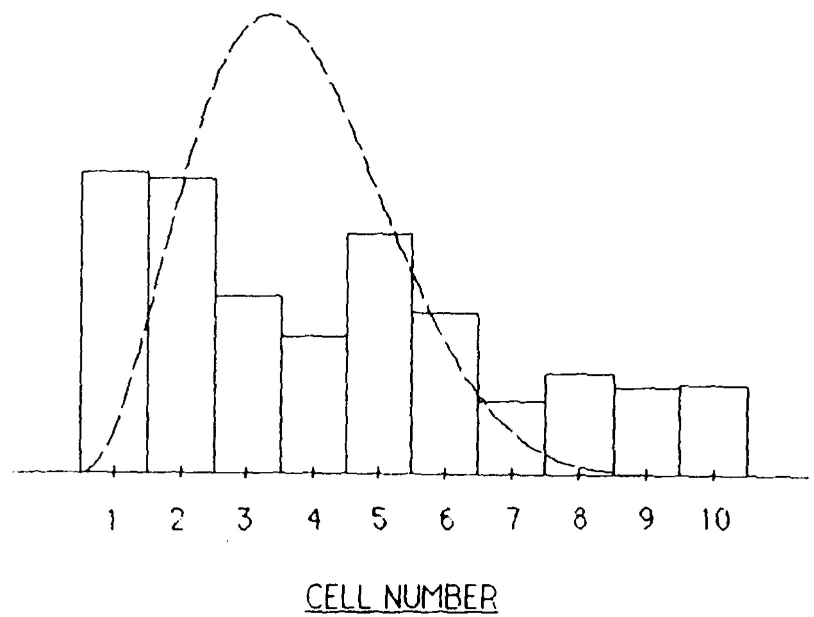

Figure 23. Beta PDF with 10% Reduced μ, 50% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN = 2.901
STANDARD DEVIATION = 1.848
MINIMUM VALUE = 1.110
MAXIMUM VALUE = 7.767
ALPHA = 0.4176
BETA = 1.1340

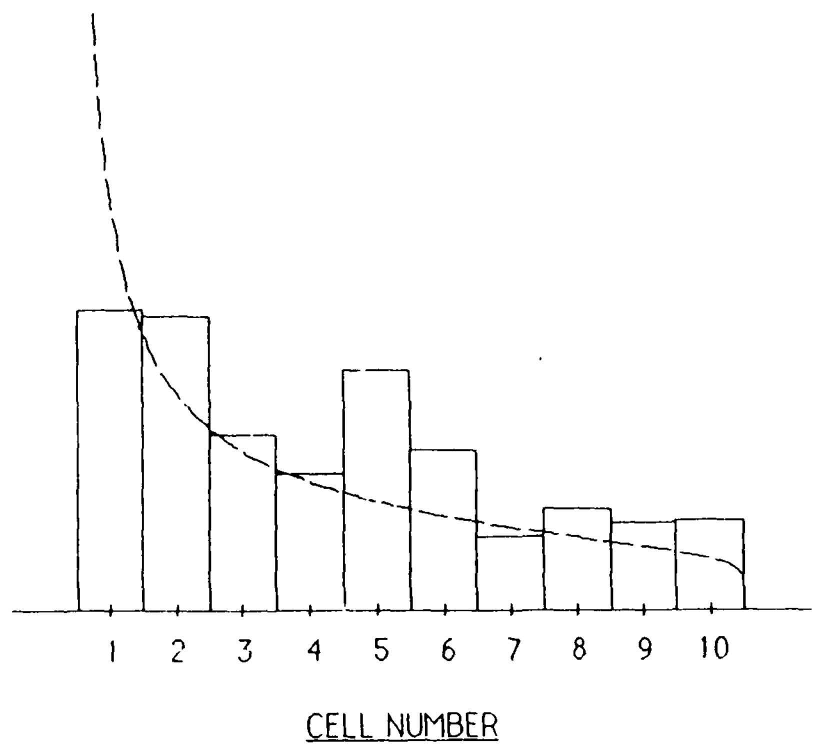

Figure 24. Beta PDF with 20% Reduced μ, 0% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN = 2.901
STANDARD DEVIATION = 1.663
MINIMUM VALUE = 1.110
MAXIMUM VALUE = 7.767
ALPHA = 0.5788
BETA = 1.5720

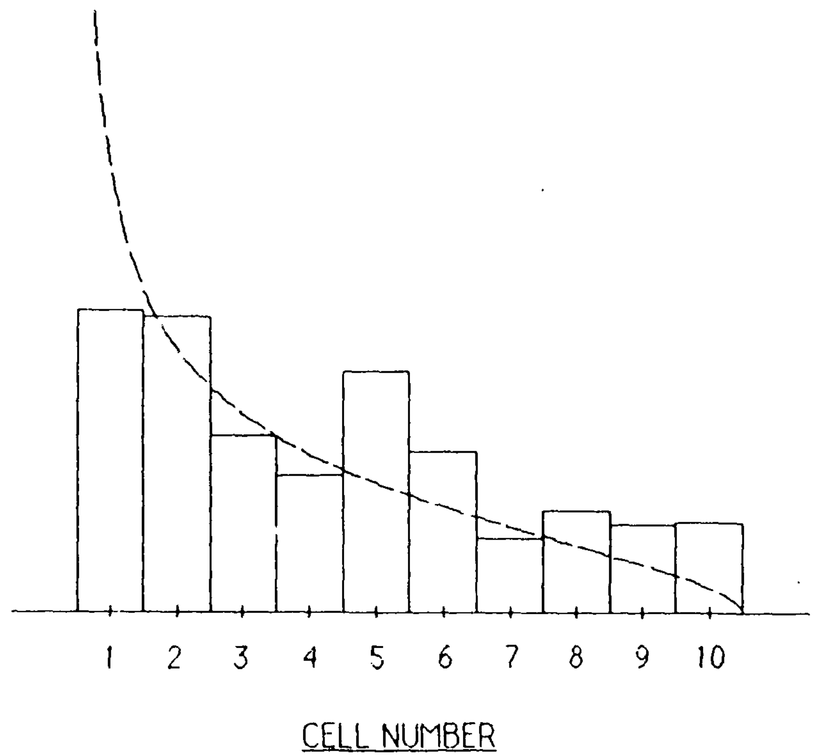

Figure 25. Beta PDF with 20% Reduced μ, 10% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940			

CELL WIDTH = 0.6657

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN = 2.901
STANDARD DEVIATION = 1.478
MINIMUM VALUE = 1.110
MAXIMUM VALUE = 7.767
ALPHA = 0.8043
BETA = 2 1850

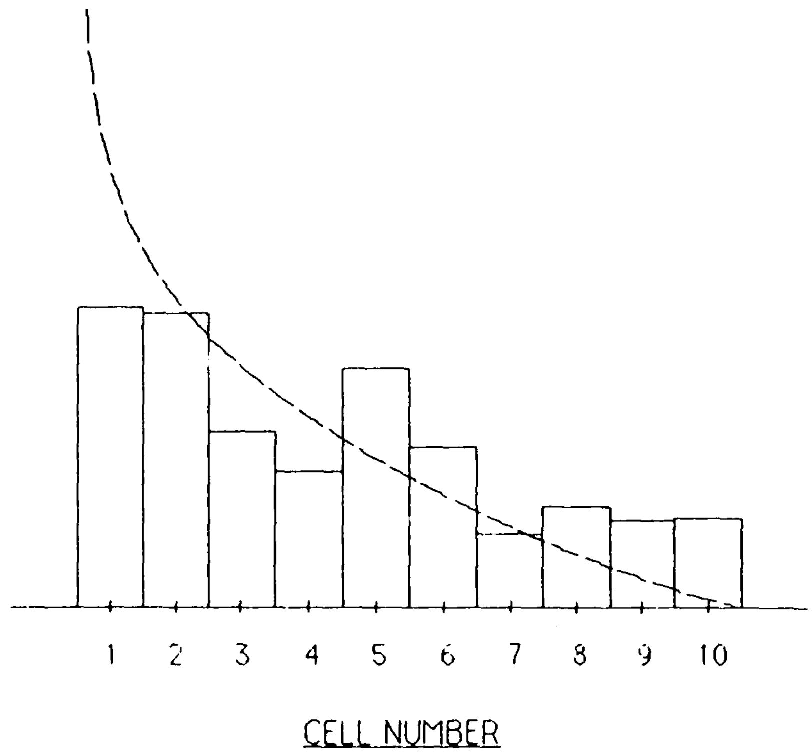

Figure 26. Beta PDF with 20% Reduced μ, 20% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1 776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5473	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN = 2.901
STANDARD DEVIATION = 0.924
MINIMUM VALUE = 1 110
MAXIMUM VALUE = 7.767
ALPHA = 2.477
BETA = 6.730

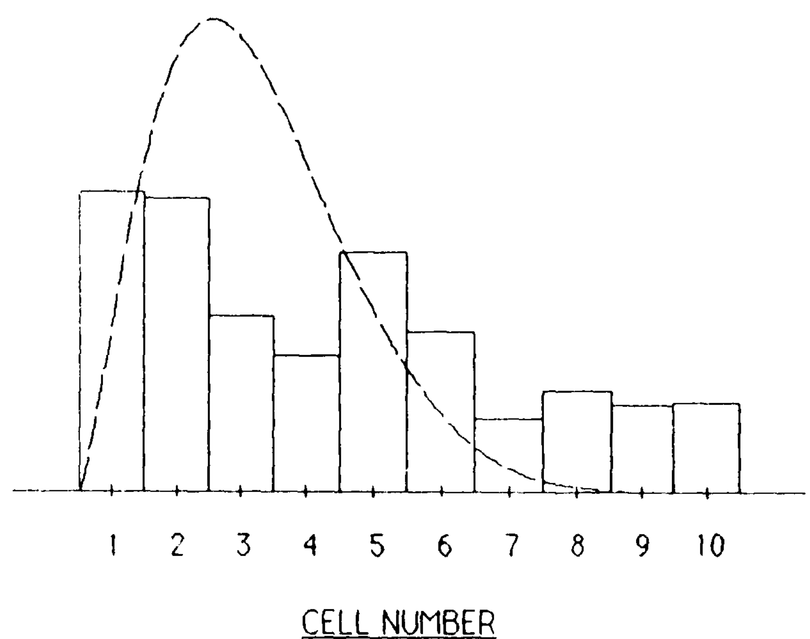

Figure 27. Beta PDF with 20% Reduced μ, 50% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN = 1.813
STANDARD DEVIATION = 1.848
MINIMUM VALUE = 1.110
MAXIMUM VALUE = 7.767
ALPHA = 0.0238
BETA = 0.2018

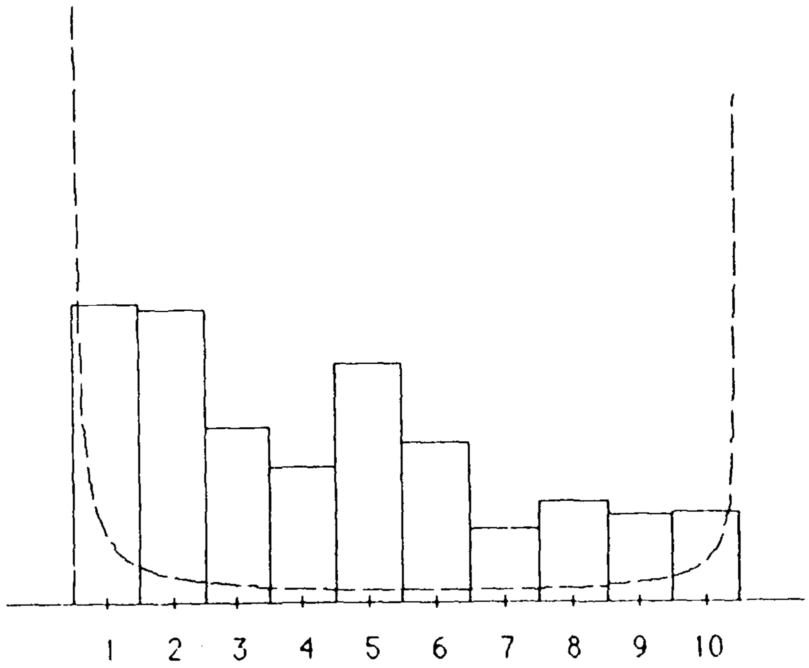

Figure 28. Beta PDF with 50% Reduced μ, 0% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940			

CELL WIDTH = 0.6657

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN	= 1.813
STANDARD DEVIATION	= 1.663
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 0.0542
BETA	= 0.4593

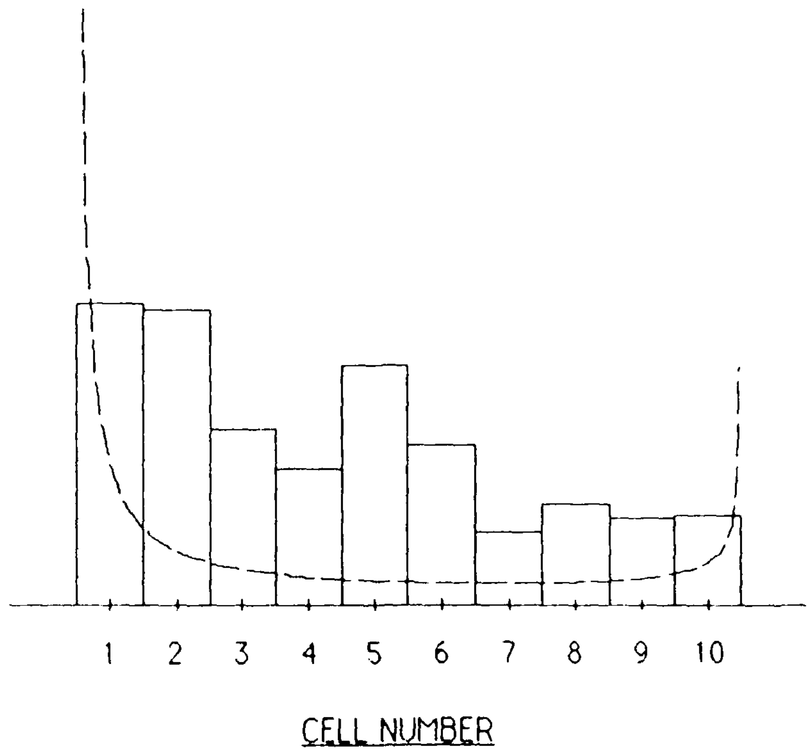

Figure 29. Beta PDF with 50% Reduced μ, 10% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940	CELL WIDTH = 0.6657		

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN	= 1.813
STANDARD DEVIATION	= 1.478
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 0.0967
BETA	= 0.8193

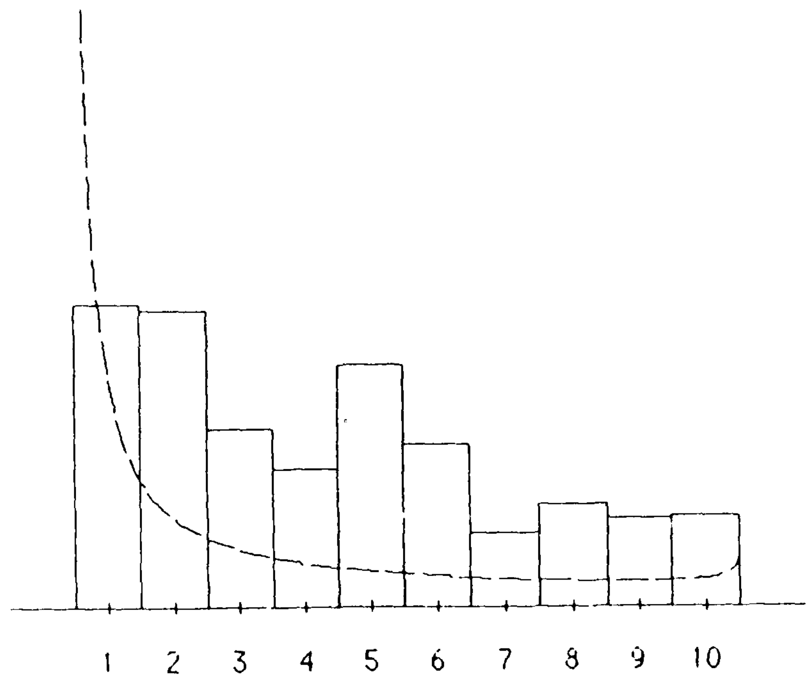

Figure 30. Beta PDF with 50% Reduced μ, 20% Reduced σ

CELL STATISTICS

CELL NUMBER	OBSERVED FREQUENCY	RELATIVE FREQUENCY	CUMULATIVE FREQUENCY	UPPER BOUND
1	170	0.1809	0.1809	1.776
2	167	0.1777	0.3585	2.441
3	100	0.1064	0.4649	3.107
4	78	0.0830	0.5479	3.773
5	136	0.1447	0.6926	4.439
6	91	0.0968	0.7894	5.104
7	41	0.0436	0.8330	5.770
8	57	0.0606	0.8936	6.436
9	49	0.0521	0.9457	7.101
10	51	0.0543	1.0000	7.767
	940			

CELL WIDTH = 0.6657

HYPOTHESIZED DISTRIBUTION: BETA

PROPOSED PARAMETERS:

MEAN	= 1.813
STANDARD DEVIATION	= 0.924
MINIMUM VALUE	= 1.110
MAXIMUM VALUE	= 7.767
ALPHA	= 0.4121
BETA	= 3.4900

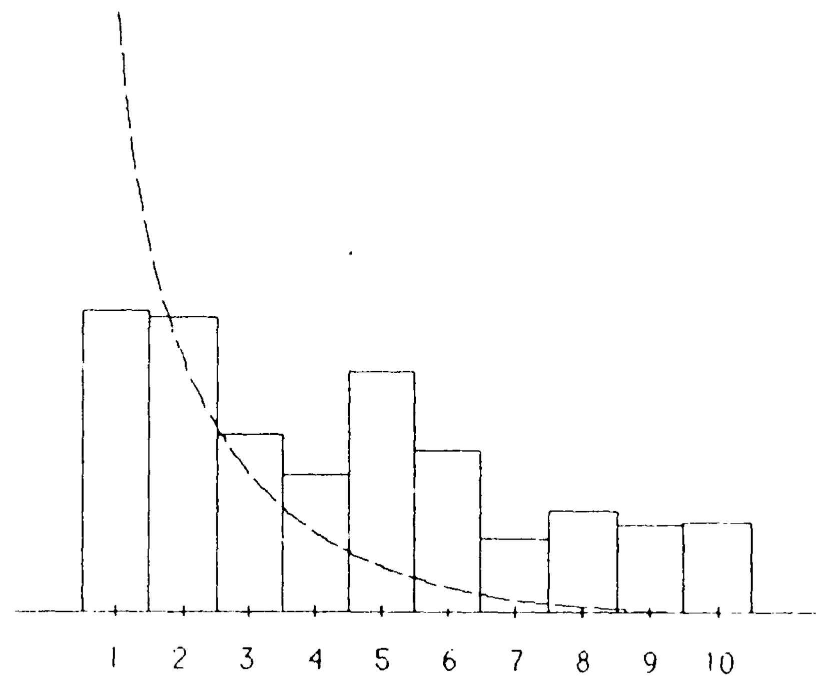

Figure 31. Beta PDF with 50% Reduced μ, 50% Reduced σ

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Vita

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AN ANALYSIS OF IN-TRANSIT LEAD TIME FOR ASSET DELIVERY AT OGDEN AIR LOGISTICS CENTER

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Philip J. Price, B.S., Capt, USAF

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Thesis Advisor: David K. Peterson
Assistant Professor
Department of Logistics Management

Approved for public release: IAW AFR 190-1.

Larry W. Emmelhainz

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Maintenance Inventory Centers (MICs) are forward stockage points for Depot Maintenance (MA) activities. AFLC has directed that the amount of material stocked in MICs be reduced. The in-transit delivery time for replenishment issues to MICs from Depot Supply has significant impact on material support concurrent with minimizing inventory levels. This study examined MIC stock replenishment in-transit time. In-transit times experienced during a six-month period in six MICs at Hill AFB, Utah (Ogden ALC) were analyzed to establish performance parameters for simulation analyses. Also, quality control tools to reduce the in-transit time and associated variability were also investigated.

Empirical in-transit time performance statistics implied the AFLC 1.5 working day delivery time standard for MIC replenishment issues was not being achieved for all MICs. Fitting empirical data to theoretical probability distributions for use in subsequent simulation experiments supported previous research that lead time data is occasionally so variable that it may not fit familiar theoretical probability distributions.

Simulation experiments indicated that the 95% line item fill rate objective outlined in certain MA data automation reports is achievable only for items characterized by high frequency of demand. The mean, variance, and probability distribution of in-transit delivery time, coupled with the current 15/7 day (stock level/reorder point) inventory policy were the main factors influencing inventory performance. Reducing the mean in-transit time improved material availability in a MIC characterized by beta-distributed in-transit delivery times.

The labor-intensive data collection required to measure the delivery process with currently available data sources is an obstacle to timely, reliable, and proactive control over the delivery process. Planned automated data systems such as the Stock Control and Distribution System must incorporate reliable and timely measurement of a MIC replenishment order's progress through the order cycle.